Region based Multimodality Image Fusion Method

Tanish Zaveri and Mukesh Zaveri

***Abstract*—This paper proposes a novel region based image fusion scheme based on high boost filtering concept using discrete wavelet transform. In the recent literature, region based image fusion methods show better performance than pixel based image fusion method. The graph based normalized cutest algorithm is used for image segmentation. Proposed method is a novel idea which uses high boost filtering concept to get an accurate segmentation using discrete wavelet transform. This concept is used to extract regions from input registered source images which is then compared with different fusion rules. The new MMS fusion rule is also proposed to fuse multimodality images. The different fusion rules are applied on various categories of input source images and resultant fused image is generated. Proposed method is applied on large number of registered images of various categories of multifocus and multimodality images and results are compared using standard reference based and nonreference based image fusion parameters. It has been observed from simulation results that our proposed algorithm is consistent and preserves more information compared to earlier reported pixel based and region based methods.**

***Index Terms*—Normalized cutset, discrete wavelet transform, high boost filter**

I. Introduction

WE use the term image fusion to denote a process by which multiple images or information from multiple images is combined. These images may be obtained from different types of sensors. With the availability of the multisensor data in many fields, such as remote sensing, medical imaging or machine vision, image fusion has emerged as a promising and important research area. In other words, Image fusion is a process of combining multiple input images of the same scene into a single fused image, which preserves full content information and also retaining the important features from each of the original images. There has been a growing interest in the use of multiple sensors to increase the capabilities of intelligent machines and systems. Actually computer systems have been developed that are capable of extracting meaningful information from the recorded data coming form the different sources. The integration of data, recorded from a multisensor system, together with knowledge, is known as data fusion [1, 2, 3, 4, 5, 6]. With the availability of the multisensor data in many fields, such as remote sensing, medical imaging or machine vision; image fusion has emerged as a promising and essential research area. The fused image should have more useful information content compared to the individual image. The different image fusion methods can be evaluated using different fusion parameters [7, 8, 9] and each parameter varies due to different fusion rule effect. In general, the parameter used to design fusion rules is based on experiments or it adaptively changes with the change in image contents so it is very difficult to get the optimal fusion effect which can preserve all important information from the source images. Image fusion system has several advantages over single image source and resultant fused image should have higher signal to noise ratio, increased robustness and reliability in the event of sensor failure, extended parameter coverage and rendering a more complete picture of the system [1]. The actual fusion process can take place at different levels of information representation. A common categorization is to distinguish between pixel, feature and decision level, although there may be crossings between them. Image fusion at pixel level amounts to integration of low-level information, in most cases physical measurements such as intensity.

The simple pixel based image fusion method is to take the average of the source images pixel by pixels which leads to undesired side effects in the resultant image. There are various techniques for image fusion at pixel level are available in literature [2, 4, 5, 6]. The region based algorithm has many advantages over pixel base algorithm like it is less sensitive to noise, better contrast, less affected by misregistration but at the cost of complexity [2]. Recently researchers have recognized that it is more meaningful to

combine objects or regions rather than pixels. Piella [3] has proposed a multiresolution region based fusion scheme using link pyramid approach. Recently, Li and young [10] have proposed multifocus image fusion using region segmentation and spatial frequency.

Zhang and Blum [4] proposed a categorization of multiscale decomposition based image fusion schemes for multifocus images. As per the literature [2, 4] large part of research on multiresolution (MR) image fusion has focused on choosing an appropriate representation which facilitates the selection and combination of salient features. The issues to be address are the specific type of MR decomposition like pyramid, wavelet, linear, morphological etc. and the number of decomposition levels. More decomposition levels do not necessarily produces better results [4] but by increasing the analysis depth neighboring features of lower band may overlap. This gives rise to discontinuities in the composite representation and thus introduces distortions, such as blocking effect or ringing artifacts into the fused image. The first level discrete wavelet transform (DWT) based decomposition is used in proposed algorithm to keep it free from disadvantages of Multiscale transform.

In this paper, a novel region based image fusion algorithm is proposed. The proposed method provides powerful framework for region based image fusion method which produces good quality fused image for different categories of images. The novelty of our algorithm lies in the way high boost filtering

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concept used to segment decomposed images using DWT. The novel fusion rule Mean Max Standard deviation (MMS) is also proposed to measure the activity level between two segmented regions of multimodality images. The normalized cut algorithm [11] is used to segment input images. The paper is organized as follows. Section 2 gives a brief introduction of DWT and normalized cut segmentation algorithm. In this section brief concept of high boost filtering also explained. Proposed algorithm is described in section 3. The brief introduction of reference based and nonreference based image fusion parameters are described brief in section 4. The simulation results are depicted in section 5. It is followed by conclusion.

II. Basic Theory

The proposed algorithm is using on discrete wavelet transform, normalized cut segmentation algorithm and high boost filtering approach which is describe brief in this section.

Wavelet Transform

Wavelet theory provides a general mathematical framework for decomposition of an image into components at different scale and with different resolutions. Wavelets are functions generated from one single function by dilations and translations [18]. The basic idea of the wavelet transform is to represent any arbitrary function as a superposition of wavelets. Any such superposition decomposes the given function into different scale levels where each level is further decomposed with a resolution adapted to that level [19]. As 2D discrete Fourier transform expands an image into a weighted sum of global cosine and sine functions, the 2D discrete wavelet transform expands an image into sum of four components at each resolution level as shown in Fig.1. The discrete wavelet transform is dividing the source image into sub images details are explained in [7]. The sub images arise from separable applications of vertical and horizontal filter. The resultant first level four image includes LL1 sub band image corresponds to coarse level approximation image and other three image includes (LH1, HL1, HH1) sub band images corresponds to finest scale wavelet coefficient detail images as shown in Fig. 1(a). To obtain the next coarse level of wavelet coefficients, the sub band LL1 alone is further decomposed. This results in two-level wavelet decomposition as shown in Fig. 1(b). Similarly, LL2 is used to obtain further decomposition. This process continues until some final scale is reached. The coefficients of transformed approximation and detail images (sub-band images) are essential features, which are useful for image fusion. The features derived from DWT transformed images are used to segment source images accurately, and are used in the next section.

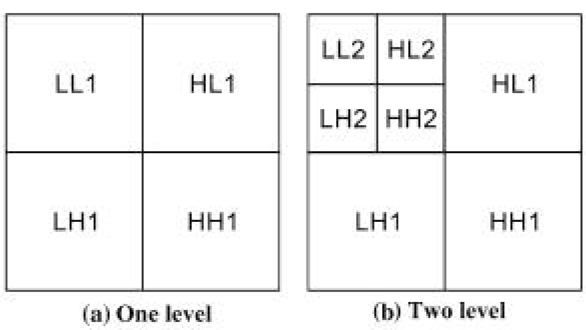

Fig. 1. Image decomposition using DWT(a)one level (b)two level

Normalized Cut segmentaion Algorithm

Recently proposed the normalized cut segmentation is used in the proposed algorithm as described in [8]. In [8], the algorithm uses on the perceptual grouping for vision problem. Rather than focusing on local features, our approach aims at extracting the global information of an image. In the proposed method, the image segmentation process is treated as a graph partitioning problem. A novel global criterion, normalized cut, is used for segmenting the graph. The normalized cut criterion can measure both the total dissimilarity and the total similarity within different groups. The output of the segmentation step is the heart of the proposed method and for implementation refers [17]. This method is used to extract segmented region. Even very small change in segmentation result can bring a huge difference to the final result so to produce accurate segmented image novel high boost filtering approach is applied..

High Boost Fitering

In our case it is desirable to emphasize high frequency components representing the image details without eliminating low frequency components to get an accurate segmentation. In this case, the high-boost filter can be used to enhance high frequency component while still keeping the low frequency components [9]. A high boost filters can be simply defined as a weighted combination of original image and the high pass filtered version of the image. It is also called as high frequency emphasis filter. The high boost filter I_{hbf} is defined as

$$I_{hbf}\text{=(K)*original image+High pass filtered image} \quad (1)$$

Weight is decided by K and weighted version of original image is added to the high pass filter image to get high boost filtered image.

III. Proposed Algorithm

In this section first framework of proposed region based image fusion method is introduced. The block diagram of proposed algorithm is shown in Fig. 2. Any region based fusion algorithm fusion results are affected by the performance of segmentation algorithm. The proposed algorithm is a novel idea to achieve accurate segmentation using high boost filtering concept. The various segmentation algorithms are available in literature [17] based on thresholding and clustering but the partition criteria used by these algorithms often generates undesired segmented regions. So in this paper, a graph based image segmentation algorithm normalized custset [11, 16] is used for image segmentation. The idea of graph based image segmentation is that the set of points are represented as a weighted undirected graph [10, 11] where the nodes of the graph are the points in the image. Each pair of nodes is connected by edge and weight on each edge is a function of similarity between nodes. In our method, a strong similarity relation between nodes is established using high boost filtering.

It also desirable to emphasize high frequency components representing the image details without eliminating low frequency components to get an accurate segmentation. In this case, the high-boost filter can be used to enhance high frequency component while still keeping the low frequency components [13]. A high boost filters can be simply defined as a weighted combination of original image and the high pass filtered version of the original image. It improves the similarity and dissimilarity of nodes in the normalized cutset segmentation algorithm which leads to an accurate segmentation. To show the efficacy of using high boost filter in our proposed method, we apply the segmentation algorithm describe in [10] on source pepsi images as shown in Fig. 3 (a) & (b). In that algorithm [10] average of two input pepsi source image is taken as an input to apply normalized cutset segmentation algorithm and results is depicted in Fig. 1(c). For the same source images, the high boost filtered image is obtained after applying DWT [12] and segmentation applied on this image and the output is presented in Fig. 3.

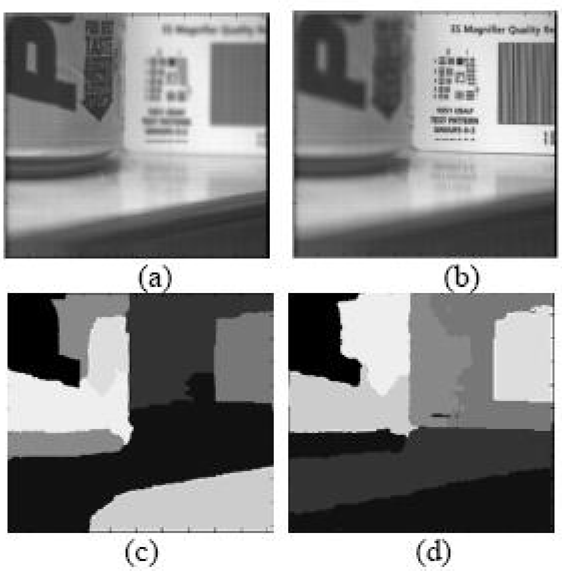

Fig. 3. Segmented Image (a) , (b) Multifocus sources of pepsi (c) Using average of both source images as input (b) Using high boost approach

The fused image can be generated by following steps as describe below.

Step1 The DWT explained in [12] is applied on image IA which gives first level decomposed image of one approximate image ($LL^1{}_A$) and three detail images ($LH^1{}_A$, $HL^1{}_A$, $HH^1{}_A$).

Step 2 The high boost image I_{A1} is generated by adding the scaled approximate image and detail images. The Normalized cut segmentation algorithm is applied on high boost image I_{A1}

$$I_{A1} = K*LL^1{}_A+LH^1{}_A+HL^1{}_A+HH^1{}_A \quad (2)$$

Where $LL^1{}_A$ is first level decomposed approximation image using DWT.$LH^1{}_A$,$HL^1{}_A$,$HH^1{}_A$ are first level decomposed detail images. Here K is weight that is used to scale $LL^1{}_A$ image.

Step 3 The output of segmentation is used to extract regions from original image IA and high boost image Ia1 generated from $LL^1{}_A$ size is not same. So Ia1 is upscale to make it equal to the size of original input image which also called as Ia1.

Step 4 Then n numbers of segmented regions are extracted from image IA and IB using segmented image Ia1 and details about n is explained later in this step when fusion rules are explained. We have used two different fusion rules to compare extracted regions from different kind of source images.

First fusion rule is based on spatial frequency (SF) which is used to identify good region extracted form multifocus source images. The SF is widely used in many literatures [10, 11] to measure the overall clarity of an image or region. The higher the spatial frequency, the more the image details are. If n^{th} region of an IA image is defined by F than , the spatial frequency of a region is calculated using Row frequency (RF) and Column frequency (CF) as described (3) and finally SF is calculated using (4).

$$RF = \sqrt{\sum\sum\left[F\left(i,j\right)-F\left(i,j-1\right)\right]^2/MN} \quad (3)$$

$$CF = \sqrt{\sum\sum\left[F\left(i,j\right)-F\left(i,j-1\right)\right]^2/MN}$$

$$SF = \sqrt{RF^2+SF^2} \quad (4)$$

SF parameter presents the quality of details in an image. The higher the value of SF, then more image details will be available in that region extracted. It is used to compare regions of Ia1 and Ib1. Intermediate fused image I_{fa1} is generated using following fusion rule 1 as described as

$$I_{fa} = \begin{cases} R_{An} & SF_{An} \geq SF_{Bn} \\ R_{Bn} & SF_{An} < SF_{Bn} \end{cases} \quad (5)$$

SF of n^{th} region of Image IA and IB is defined d as SF_{An} and SF_{Bn} respectively. Here n is a number of regions and it varies from 1 to i. where n = 1, 2, 3,...i. The value of i equals to 9 determined after analyzing many simulation results. Regions from image IA and IB are represented as R_{An} and R_{Bn} respectively. I_{fa1} is resultant fused image after applying fusion rule-1 as described in (6). This rule is not enough to capture desired region from all the type of source images. So new statistical parameter based fusion rule Mean Max Standard deviation (MMS) is introduced.

MMS is an effective fusion rule to capture desired information from multimodality images. This proposed fusion rule exploits standard deviation & mean value of images. The MMS is described as

$$MMS_{An} = ME_{An}/SD_{An}*R_{An}max \quad (6)$$

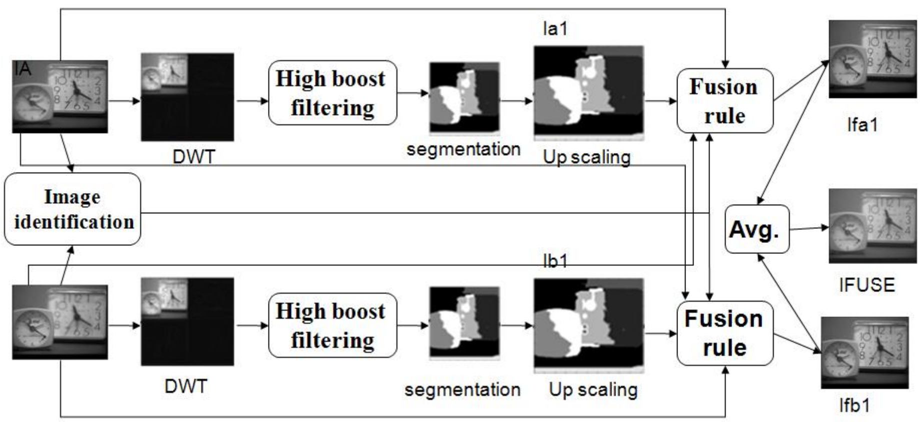

Fig. 2. Block Diagram of proposed method

Where ME_{An},SD_{An},$\mathrm{R}_{An}max$ are mean, standard deviation and maximum intensity value of nth segmented region of image IA respectively.The advantage of using MMS is that it provides a good parameter to extract a region with more critical details. This evident from simulation results described later in this paper. MMS based fusion rule is very important in the case of multimodality images shown in Fig. 3. This is evident from the following example. In this example, two source images (i) using visual camera & (ii) using IR camera for surveillance application as shown in Fig. 3 (a) & (b) respectively. In visual image, background is visible but a person is not visible which is an object of interest. In IR image this man is visible.

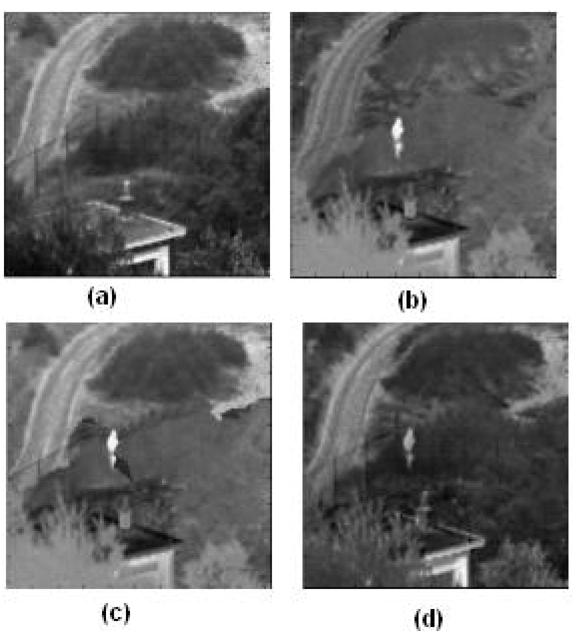

Fig. 4. Fusion results for multimodality IR image (a) visible source image (b) IR source image (c) Region method (d) Proposed method

From our study, it is analyzed that with visual images, SD is high and ME is low where in images captured using sensors like MMW & IR have ME value high & SD is low so in our algorithm we have used both SD & ME with maximum intensity value RAn max to derive new parameter MMS. From the experiments, it is observed that the low value of MMS is desired to capture critical regions from the sensor images. The fusion rule 2 is described as below

$$I_{fa} = \begin{cases} R_{An} & MMS_{An} \geq MMS_{Bn} \\ R_{Bn} & MMS_{An} > MMS_{Bn} \end{cases} \tag{7}$$

Intermediate fused image Ifa1 is generated by fusion rule 2 which is applied for multimodality images and first fusion rule is applied for multifocus images. In Fig. 4(c), only region based image fusion algorithm is applied as described in [10] with SF fusion rule. The fusion result generated after applying MMS fusion rule is shown in the Fig. 4 (d). It is clearly seen from the results that the MMS rule is very effective to generate good quality fused image for multimodality source images.

Step 5 Repeat the step 1 to 4 for image IB and generate intermediate fused image I_{fb1}

Step 6 Both I_{fa1} and I_{fb1} are averaged to improve the resultant fused image IFUSE.

This new framework of proposed algorithm avoids the shift variance problem because inverse wavelet transform is not required in our algorithm. The high boost image concept is applied to generate accurate segmented image. The graph theory based normalized cut segmentation algorithm is used in proposed algorithm which can extract the regions from the decomposed image. The activity level measured in each region is decided by the spatial frequency and novel MMS statistical parameter which is used to generate good quality fused image for all categories of multimodality and multifocus images. The next section describes image fusion evaluation criteria in brief.

IV. Evaluation Criteria for Fused image

Any image fusion algorithm can be assessed using two categories of performance measurements parameters which are subjective and objective which may further divided into reference and non reference quality assessment parameters.

Subjective indices rely on the ability of peoples comprehension and are hard to come into application. While objective indices can overcome the influence of human vision, mentality and knowledge, and make machines automatically select a superior algorithm to accomplish the mission of image fusion. Objective indices can be divided into three categories based on subjects reflected. One category reflects the image features, such as entropy, spatial frequency and gradient. The second reflects the relation of the fusedimage to the source images, such as mutual information. The third reflects the relation of the fused image to the reference image, such as cross entropy, correlation coefficient, Root mean square error (RMSE). We have used each category of fusion parameter to evaluate our final fused image.

A. Refrence Based Image Fusion Parameters

Most widely used reference based image fusion performance parameters are Entropy, Structural similarity Matrix (SSIM), Quality Index (QI), Mutual Information (MI), Root mean square error (RMSE).

A.1 Root mean square error

The Root mean square error (RMSE) is well known parameter to evaluate fused image. It represents amount of deviation present in fused image compared to reference image [14]. The RMSE is calculated between fused image F and standard reference image R which is defined as

$$RSME = \sqrt{\sum \sum \left[R\left(i,j\right) - F\left(i,j\right) \right]^2 / MN} \qquad (8)$$

A.2 Mutual Information

Mutual information (MI) indices also used to evaluate the correlative performances of the fused image and the reference image as explained in [9]. Let A and B be two random variables with marginal probability distributions P_A(a) and P_B(b), and joint probability distribution P_{AB}(a,b), mutual information is defined as

$$MIr_{AB} = \sum P_{AB}\left(a,b\right) . \log\left(P_{AB}\left(a,b\right) / P_A\left(a\right) P_B\left(b\right)\right) \quad (9)$$

A higher value of mutual information (MI) indicates that the fused image contains fairly good quantity of information presented in fused image compared to refrence which is defined as MIr. A higher value of mutual information (MIr) represents more similar the fused image compared to reference image.

The structural similarity index measure (SSIM) proposed by Wang and Bovik [15] is based on the evidence that human visual system is highly adapted to structural information and a loss of structure in fused image is indicating amount of distortion present in fused image. It is designed by modeling any image distortion as a combination of three factors; loss of correlation, radiometric distortion, and contrast distortion as mention in [8, 9]. The dynamic range of SSIM is [-1, 1]. The higher the value of SSIM indicates more similar structures in fused and reference image. If two images are identical, the similarity is maximal and equals 1.

B. Non Refrence Based Image Fusion Parameter

The Mutual information (MI), the objective image fusion performance metric $Q^{AB/F}$, spatial frequency (SF) [10] and entropy [14] are important image fusion parameters to evaluate quality of fused image when reference image is not available.

MI described in A.2 & in (9) can also be used to evaluate fused images without the reference image by computing the MI between source image IA and fused image IFUSE called as I_{AF} and similarly find I_{BF} using image IB as a source image and calculate total MI as defined by

$$MI = I_{AF} + I_{BF} \qquad (10)$$

B.1 Objective Image Fusion Performance Measure

The goal in pixel level image fusion is to combine and preserve in a single output image all the important visual information that is present in a number of input images. Thus an objective fusion measure should (i) extract all the perceptually important information that exists in the input images and (ii) measure the ability of the fusion process to transfer as accurately as possible this information into the output image. In this work we associate important visual information with the edge information that is present in each pixel of an image. Notice that this visual to edge information association is supported by Human Visual System [20] studies and is extensively used in image analysis and compression systems. The objective image fusion performance metric $Q^{AB/F}$ which is proposed by Xydeas and Petrovic [7] reflects the quality of visual information obtained from the fusion of input

images and can be used to compare the performance of different image fusion algorithm. Furthermore, by evaluating the amount of edge information that is transferred from input images to the fused image, a measure of fusion performance can be obtained. Consider two input images A and B, and a resulting fused image F. Note that the following methodology can be easily applied to more than two input images. A Sobel edge operator is applied to yield the edge strength g(n,m) and orientation $\alpha\left(n,m\right)$ information for each pixel p(n,m), $1 \le n \le N$ and $1 \le m \le M$ Thus for an input image A edge strength g(n,m) and orientation $\alpha\left(n,m\right)$ is defined as [7]

$$g_A\left(n,m\right) = \sqrt{S_A^x\left(n,m\right)^2 + S_A^y\left(n,m\right)^2} \qquad (11)$$

$$\alpha_A\left(n,m\right) = \arctan\left(S_A^y\left(n,m\right) / \left(S_A^x\left(n,m\right)\right)\right) \qquad (12)$$

where $s_A^x\left(n,m\right)$ and $s_A^y\left(n,m\right)$ are the output of the horizontal and vertical Sobel templates centered on pixel $P_A\left(n,m\right)$ and convolved with the corresponding pixels of image A. The relative strength and orientation values of $G^{AF}\left(n,m\right)$ and $A^{AF}\left(n,m\right)$ of an input image A with respect to F are formed as [7]. SF is defined in the proposed algortim section II. The entropy is also used to evaluate fused image as described below

$$G^{AF}(n,m) = \begin{cases} \frac{g_F(n,m)}{g_A(n,m)}, \text{if } g_A(n,m) > g_F(n,m) \\ \frac{g_A(n,m)}{g_F(n,m)}, \text{otherwise} \end{cases} \quad (13)$$

$$A^{AF}(n,m) = || \alpha_A(n,m) \alpha_A(n,m) | - \Pi/2| / \Pi/2 \quad (14)$$

These are used to derive the edge strength and orientation preservation values

$$Q_g^{AF}(n,m) = \Gamma_g / 1 + e^{k_g \left(G^{AF}(n,m) - \sigma_g\right)} \quad (15)$$

$$Q_\alpha^{AF}(n,m) = \Gamma_g / 1 + e^{k_\alpha \left(A^{AF}(n,m) - \sigma_\alpha\right)} \quad (16)$$

$Q_g^{AF}(n,m)$and $Q_\alpha^{AF}(n,m)$ model perceptual loss of information in F, in terms of how well the strength and orientation values of a pixel p(n,m) in A are represented in the fused image. The constants Γ_g,κ_g,σ_g and Γ_α, κ_α, σ_α determine the exact shape of the sigmoid functions used to form the edge strength and orientation preservation values, see equations (15) and (16). Edge information preservation values $Q^{AB/F}$ is then defined as

$$Q^{AB/F}(n,m) = \sum_{n=1}^{N}\sum_{m=1}^{M} Q^{AF}(n,m) W^A(n,m) + Q^{BF}(n,m) W^B(n,m) / \sum_{i=1}^{N}\sum_{j=1}^{M} \left(W^A(i,j) + W^B(i,j)\right) \quad (17)$$

with $0 \leq Q^{AF}(n,m) \leq 1$. A value of 0 corresponds to the complete loss of edge information, at location (n,m), as transferred from A into F.$Q^{AF}(n,m) = 1$ indicates "fusion" from A to F with no loss of information.

B.3 Information Entropy

Entropy is an index to evaluate the information quantity contained in an image. The entropy of the fused image F is defined as

$$E = -\sum_{i=0}^{L-1} Pi(f) \log_2 Pi(f) \quad (18)$$

Where p is the normalized histogram of the fused image to be evaluated in our case it is IFUSE, L is maximum value for a pixel in the image which defines the total of grey levels. The entropy issued to measure the overall information in the fused image. The larger the entropy value better the fusion results. The simulation results are discussed in detail in the next section.

V. Experimental Results and Discussion

The novel region based image fusion algorithm described in previous section has been implemented using Matlab 7. The proposed algorithm are applied and evaluated using large number of dataset images which contain broad range of multifocus and multimodality images of various categories like multifocus with only object, object plus text, only text images and multi modality IR (Infrared) and MMW (Millimeter Wave) images to verify the robustness of an algorithm and simulation results are shown in Fig. 5 to 10.

In the proposed method, high boost filtering approach is used to increase the accuracy of segmentation and as described in (1) are used with the K equal to 5 for pair of multimodality images and K equal to 2 for pair of multifocus images. These values are determined after analyzing the simulation results of many experiments which improve the visual quality of final fused image. The performance of proposed algorithm evaluated using standard reference based and nonreference based image fusion evaluation parameters explained in previous section and proposed algorithm simulation results are compared with earlier reported region based [5] and pixel based image fusion algorithm [10] and simulation results are depicted in Table I, II and III.

A. Fusion Resutls of multi-focus images

The multifocus images available in our dataset are of three kinds (1) object images (2) only text images and (3) object plus text images which are shown in Fig. 5 (a) & (b) clock image, Fig. 6 (a) & (b) text image, Fig. 8 (a) & (b) pepsi image and Fig. 8 (a) & (b) book image respectively. In Fig. 5 to 8 column (a) multifocus images, left portion is blurred and in column (b) of same figure, right portions of images is blurred and column (c) shows the corresponding fused image obtained by applying proposed method and column (d) and (e) are resultant fused image obtained by applying pixel based DWT method proposed by Wang [5] and region based fusion method proposed by Li and Yang [10]. The visual quality of the resultant fused image of proposed algorithm is better than the fused image obtained by other compared methods. The reference based and non reference based image fusion parameters comparisons are depicted in Table I and Table II. All reference based image fusion parameters SF, MIr, RMSE and SSIM are significantly good for proposed algorithm compared to other methods as depicted in Table I. Also non reference based image fusion parameters as depicted in Table II are better than compared methods. In Table II, SF and $Q^{AB/F}$ are remarkably better than other compared fusion methods which also evident from the visual quality of resultant fused image.

B. Fusion of infrared and MMW images

The effectiveness of the proposed algorithm can be proved by extending it to its application to the multimodality concealed weapon detection (MMW images) and IR images. MMW camera image with the gun is shown in Fig. 9 (b) and

(a) (b) (c) (d) (e)

Fig. 5. Fusion results of multi-focus image of clock (a), (b) Multi-focus source images (c) Proposed method (d) DWT method (e) Region method

(a) (b) (c) (d) (e)

Fig. 6. Fusion results of multi-focus image of text (a), (b) Multi-focus source images (c) Proposed method (d) DWT method (e) Region method

(a) (b) (c) (d) (e)

Fig. 7. Fusion results multi-focus image of pepsi (a), (b) Multi-focus source images (c) Proposed method (d) DWT method (e) Region method

(a) (b) (c) (d) (e)

Fig. 8. Fusion results multi-focus image of book (a), (b) Multi-focus source images (c) Proposed method (d) DWT method (e) Region method

(a) (b) (c) (d) (e)

Fig. 9. Fusion results for multimodality MMW image (a) Visual image (b) MMW image (c) Proposed method (d) DWT method (e) Region method

Fig. 10. Fusion results for multimodality IR image (a) visible source image (b) IR source image (c) Proposed method (d) DWT method (e) Region method

TABLE I
IMAGE FUSION PARAMETERS FOR REFERENCE BASED IMAGES

Image	Fusion Methods	Fusion Parameters			
		SF	MI	RMSE	SSIM
Pepsi Image	DWT Based [5]	11.6721	2.5208	6.6722	0.9364
	Region Based[10]	13.5320	2.7035	4.8129	0.9749
	Proposed Method	13.5934	3.0868	3.1691	0.9910
Book Image	DWT Based [5]	23.5505	3.2573	12.2942	0.9135
	Region Based [10]	31.3459	3.5747	5.9062	0.9785
	Proposed Method	31.5482	3.6607	5.3855	0.9820

TABLE II
IMAGE FUSION PARAMETERS FOR NON REFERENCE BASED IMAGES

Image	Fusion Methods	Fusion Parameters			
		SF	MI	$Q^{AB/F}$	Entropy
Clock Image	DWT Based [5]	8.1506	6.4403	0.5696	8.1506
	Region Based[10]	10.3350	6.9279	0.7119	8.7813
	Proposed Method	10.0048	7.7344	0.7018	8.8066
Text Image	DWT Based [5]	8.1956	2.9235	0.5317	5.6600
	Region Based [10]	10.4058	2.9647	0.7311	5.6426
	Proposed Method	11.1208	3.4192	0.7711	5.8867

visible images of a group of persons are shown in Fig. 9 (a). Here the aim is to detect gun location in the image by using the visible image.

In visual camera image details of surrounding area can be observed in shown Fig. 10 (a) and IR camera detect the human in captured image as shown in Fig. 10 (b). The aim of applying fusion algorithm on IR image is to detect the human and its location using both source images information. The visual quality of resultant fused images for both the cases of proposed algorithm is better than other methods new MMS fusion rule is used in proposed algorithm which also evident by evaluating the Table III. The entropy is significantly better than region based methods as depicted in Table III.

TABLE III
MULTIMODALITY IMAGE FUSION RESULTS

Image	fusion Method	Entropy
Ir Image	DWT Based	6.742
	Region Based	6.0472
	Proposed Method	6.7861
MMW Image	DWT Based [5]	4.9802
	Region Based [10]	3.7593
	Proposed Method	7.3931

Entropy is considered to evaluate the final fusion results of both IR and MMW multimodality source images because both the case IR and MMW sensor source images are blurred and in that case SF and $Q^{AB/F}$ do not give significant values for comparison. The simulated results depicted in Table I, II and III shows that proposed method is performing well than other compared methods for broad categories of multifocus and multimodality images.

VI. Conclusion

In this paper, new region based image fusion method using high boost filtering concept is described. This novel idea is applied on large number of dataset of each category and simulation results are found with superior visual quality compared to other earlier reported pixel and region based image fusion method. Here two different fusion rules are applied on broad range of images. The novel MMS fusion rule is introduced to select desired regions from multimodality images. Proposed algorithm is compared with standard reference based and non-reference based image fusion parameters and from simulation and results, it is evident that our proposed algorithm preserves more details in fused image. There are number of other advantages of proposed algorithm (1) The segmentation algorithm is applied on decomposed image which is of less size compared to original image so less computation time required to segment source image (2) As inverse DWT is not required to generate final fused image, so algorithm is free from shift invariance problem (3) Because of high boost filtering approach accurate segmentation is expected so proposed method performance will not degraded as image content change so algorithm is not image content dependent (4) Region based algorithms are less sensitive to noise, misregistration, contrast change so proposed algorithm has this advantage. Algorithm can be further extended by applying it to other categories of images like medical images and satellite images.

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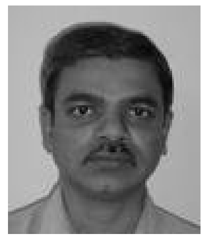

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