A NOVEL REGION BASED IMAGE FUSION METHOD USING DWT AND REGION CONSISTENCY RULE

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Abstract: This paper proposes a novel region based image fusion scheme using discrete wavelet transform and region consistency rule. In the recent literature, region based image fusion methods show better performance than pixel based image fusion methods. The graph based normalized cutset algorithm is used for image segmentation. The region consistency rule is used to select the regions from discrete wavelet transform decomposed source images. The new MMS fusion rule is also proposed to fuse multimodality images. 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 that simulation results of our proposed algorithm are consistent and more information is preserved compared to earlier reported pixel based and region based methods.

1 INTRODUCTION

In the recent years image fusion has emerged as an important research area because of its wide application in many image analysis task such as target recognition, remote sensing, wireless sensor network and medical image processing. 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. There has been a growing interest in the use of multiple sensors to increase the capabilities of intelligent machines and systems. Actually the computer systems have been developed those are capable of extracting meaningful information from the recorded data coming from the different sources. 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 retains the important features from each of the original images. The integration of data, recorded from a multisensor system, together with knowledge, is known as data fusion (Devid, 2001). Because of the limited depth of focus in digital camera, one part of the object is well focused while the other parts are being out of focus. Parts of the image which are out of focus have less depth of field so in order to get all the detailed information from out of focus area, the image fusion method is used. The image fusion method is used to combine relevant information from two or more source images into one single image such that the single image contains most of the information from all the source images. Most of advance sensors used in recent years have capability to produce an image. The sensors like optical cameras, millimetre wave cameras, infrared cameras, x-ray cameras and radar cameras are examples of it. In this paper, IR camera and MMW camera images are used to apply our proposed method.

Image fusion methods (Piella, 2003) are classified mainly into two categories: (i) pixel based and (ii) region based. Pixel based methods generally deal with pixel level information directly. In pixel based image fusion method, the average of the source images is taken pixel by pixel. However this

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leads to undesired side effects in the resultant image. There are various techniques for image fusion at pixel level available in literature (Zhong, 1999) (Anna, 2006). The region based algorithm has many advantages over pixel base algorithm. It is less sensitive to noise, better contrast, less affected by misregistration but at the cost of complexity (Piella, 2003). Researchers have recognized that it is more meaningful to combine objects or regions rather than pixels. Piella (Piella, 2002) has proposed a multiresolution region based fusion scheme using link pyramid approach. Recently, Li and Young (Shutao, 2008) have proposed region based multifocus image fusion method using spatial frequency as a fusion rule.

Zhang and Blum (Zhong, 1999) had proposed a categorization of multiscale decomposition based image fusion schemes for multifocus images. As per the literature, large part of research on multiresolution (MR) image fusion has emphasized on choosing an appropriate representation which facilitates the selection and combination of salient features. The issues to be addressed are how to choose the specific type of MR decomposition methods like pyramid, wavelet, morphological etc. and the number of decomposition levels. More decomposition levels do not necessarily produce better results (Zhong, 1999) but by increasing the analysis depth, neighbouring 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 mitigate the drawback of Multiscale transform. Also a region is more meaningful structure in multifocus image and it has many advantages over pixel based algorithm. Proposed algorithm uses region based approach. The heart of our algorithm is the segmentation of an image. The normalized cut based (Shi, 2000) image segmentation method is used in proposed algorithm. The new region consistency and mean max and standard deviation (MMS) fusion rule are proposed in this algorithm to improve the fusion image quality.

The paper is organized as follows. Proposed algorithm is described in the following section. The reference based and nonreference based image fusion evaluation parameters are introduced in section 3. The simulation results and assessment are described in Section 4. It is followed by the conclusion.

2 PROPOSED ALGORITHM

In this section first framework of proposed region based image fusion method using DWT and region consistency rule is introduced. The discrete wavelet transform divides the source image into sub images details are explained in (Mallat, 1989). The sub images arise from separable applications of vertical and horizontal filter. The resultant first level decomposed four images include LL_1 sub band image corresponding to coarse level approximation image. Also the other three decomposed image include (LH_1, HL_1, HH_1) sub band images corresponding to finest scale wavelet coefficient detail images. Most image fusion method based on DWT apply max or average fusion rule on DWT decomposed approximate and detailed images to generate final fused image. This fusion rule based on DWT produces significant distortion in final fused image as described in Fig. 1.

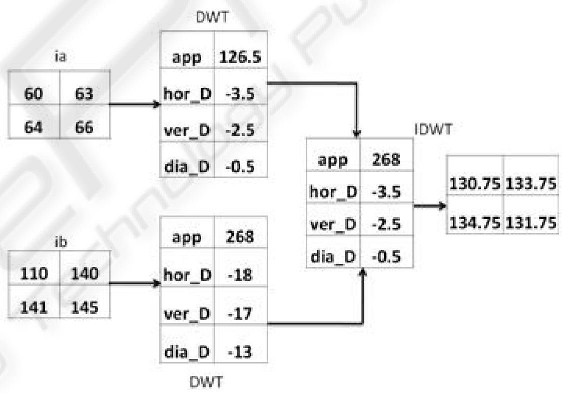


Figure 1: DWT computation process for fusion.

In Fig. 1, two image ia & ib of 2 x 2 size are considered as the input source images. After applying DWT, image is decomposed into four components which are represented app, hor_D, ver_D and dia_D. Among these four coefficients; one app is approximate coefficient and hor_D, ver_D and dia_D are three detail coefficients as shown in the Fig. 1. Now if we apply Max rule to select fused coefficient to decomposed images; hor_D, ver_D, dia_D coefficient will be selected from image ia while approximate coefficient will be selected from image ib. So when inverse DWT is applied on these images, it adds undesired information distortion in final fused image. After applying inverse DWT, the pixel values of resultant fused matrix are shown in Fig. 1 which is not related to any of the input images and the difference between two pixels also changed. Therefore, it is

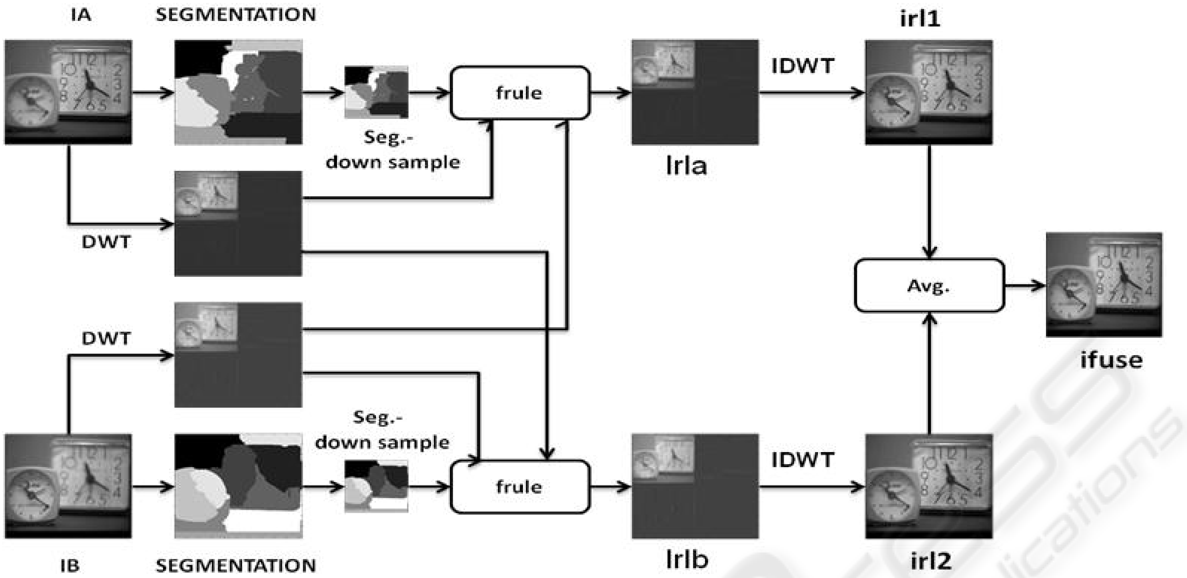


Figure 2: Block diagram of the proposed method.

necessary to design a technique which can solve this problem and generate consistent pixel value related to either of the input images. The effect of this problem is more severe in region based image fusion scheme. To solve this problem region consistency rule is introduced in the proposed method which is explained in detail later in this section. The block diagram of proposed algorithm is shown in Figure 2. The fused image can be generated by following steps as describe below.

Step 1 The DWT explained in (Gonzalez, 2006) is applied on image IA which gives first level decomposed image of one approximate image (LL_{1A}) and three detail images (LH_{1A}, HL_{1A}, HH_{1A}).

Step 2 The Normalized cut segmentation algorithm is applied on image IA. Segmentation is then down sampled to match the size of DWT decomposed image.

Step 3 The n numbers of segmented regions are extracted from approximate component of image IA and IB using segmented image. How the value of n is decided 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. The SF is widely used in many literatures (Shutao, 2008) to measure the overall clarity of an image or region. The n^{th} region of an IA image is defined by RA_n. The spatial frequency of that region is calculated using Row frequency (RF) and Column frequency (CF) as described in (1) and finally SF is calculated using (2). SF parameter presents the quality of details in an image. Higher the value of SF, more details of image are available in that region extracted. First fusion rule is region based image fusion rule with spatial frequency (SF) as described in (3), which is used to identify good quality region extracted from multifocus source images and image I_{rla1} is generated. SF of nth region of Image IA and IB is defined as SF_{An} and SF_{Bn} respectively.

$$\mathrm{RF} = \sqrt{\frac{\sum\sum[\mathrm{F(i,j)-F(i,j-1)}]^2}{\mathrm{MN}}} \qquad \mathrm{CF} = \sqrt{\frac{\sum\sum[\mathrm{F(i,j)-F(i-1,j)}]^2}{\mathrm{MN}}} \tag{1}$$

$$\mathrm{SF} = \sqrt{\mathrm{RF}^2+\mathrm{SF}^2} \tag{2}$$

$$I_{rla1} = \begin{cases} RA_{An} & SF_{An} \geq SF_{Bn} \\ RA_{Bn} & SF_{An} < SF_{Bn} \end{cases} \tag{3}$$

Here *An* and *Bn* are number of regions in image IA and IB respectively. The value of n varies from 1 to i, where n = {1, 2, 3….i}. The value of i equals to 9 produces best results and it is determined after analyzing many simulation results of various categories of source image dataset. Regions extracted after applying normalized cut set segmentation algorithm on approximate image LL_{1A} are represented as RA_{An} and RA_{Bn} respectively. I_{rla1}

is resultant fused image after applying fusion rule 1 as described in (3). This rule or any other existing fusion parameter is not enough to capture desired region from all the type of source images especially multisensor images so new mean max and standard deviation (MMS) rule is proposed in our algorithm.

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

$$MMS_{An} = ME_{An} / SD_{An} * R_{An\,\max} \qquad (4)$$

Where ME_{An}, SD_{An} are mean, standard deviation of nth region of image LL_{1A} and R_{Anmax} is maximum intensity value of same region of image LL_{1A}. The advantage of using MMS is that it provides a good parameter to extract a region which has more critical details.

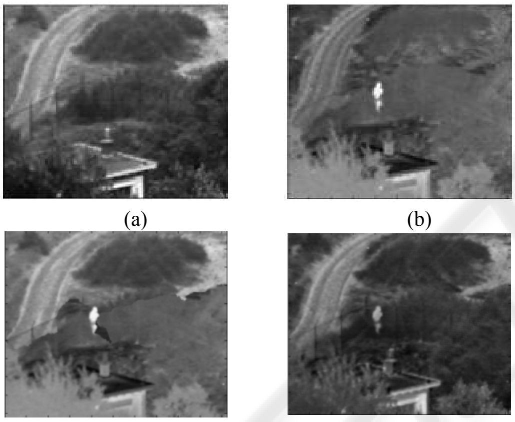


Figure 3: Input source multimodality IR image (a) visual image (b) IR image ((c) Region method (d) Proposed method.

This evident from simulation results described later in this paper. MMS based fusion rule is very important in the case of multimodality multisensor images shown in Figure 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 an object of interest is. In IR image this man is visible.

From our study, it is analyzed that for visual images, SD is high and ME is low where in multisensor 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 R_{Anmax} to derive new parameter MMS. From the experiments, it is observed that the low value of MMS is desired to capture critical regions especially man in this multisensor images. The fusion rule 2 is described as below

$$I_{rla1} = \begin{cases} RA_{An} & MMS_{An} \le MMS_{Bn} \\ RA_{Bn} & MMS_{An} > MMS_{Bn} \end{cases} \qquad (5)$$

Intermediate fused image I_{rla1} is generated by fusion rule 2 which is applied for multimodality images and first fusion rule is applied for multifocus images. In Fig. 3(c), only region based image fusion algorithm is applied as described in (Shutao, 2008) with SF fusion rule. The fusion result generated after applying MMS fusion rule is shown in the Fig. 3 (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. After taking approximate component by above method, region consistency rule is applied to select detail component from both decomposed images, which is described in (6).

Region consistency rule states that chose detail components from the results of fusion rule 1 of approximate component.

$$I_{rlv1} = \begin{cases} RD_{An} & \text{if } I_{rla1}=RA_{An} \\ RD_{Bn} & \text{if } I_{rla1}=RA_{Bn} \end{cases} \qquad (6)$$

Where I_{rlv1} is first region of vertical component of image HL_{1A}. Similarly I_{rlh1} and I_{rld1} is computed from image LH_{1A} and HH_{1A} respectively. If after applying fusion rule first region is selected from image IA then all the detail component regions are also selected from the same image IA. Fused Images generated with and without applying region consistency rule are shown in Fig. 4 (c) & (f) respectively.

Step 4 IDWT is performed to generate Irl1.

Step 5 Repeat the step 1 to 4 for image IB and generate intermediate fused image Irl2

Step 6 Both Irl1 and Irl2 are averaged to improve the resultant fused image IFUSE.

This new frame work is an efficient way to improve the consistency in final fused image and it avoids distortion due to unwanted information added without using region consistency rule. 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.

3 EVALUATION PARAMETERS

We evaluated our algorithm using two categories of performance evaluation parameters; subjective and objective for the set of images of various categories. The objective image fusion parameters are further divided into reference and non reference based quality assessment parameters. Fusion performance can be measured correctly by estimating how much information is preserved in the fused image compared to source images.

3.1 Reference 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). The RMSE and Entropy are well known parameters to evaluate the amount of information present in an image (Gonzalez, 2006). Mutual information (MI) indices are also used to evaluate the correlative performances of the fused image and the reference image as explained in (Zheng, 2006) which is used in this paper as MIr. A higher value of mutual information (MIr) represents more similar fused image compared to reference image.

The structural similarity index measure (SSIM) proposed by Wang and Bovik (Zhou, 2002) is based on the evidence that human visual system is highly adapted to structural information and a loss of structure in fused image indicates amount of distortion present in fused image. It is designed by modelling any image distortion as a combination of three factors; loss of correlation, radiometric distortion, and contrast distortion as mentioned in (Zhou, 2002). The dynamic range of SSIM is [-1, 1]. The higher value of SSIM indicates more similar structures between fused and reference image. If two images are identical, the similarity is maximal and equals 1.

3.2 Non Reference Based Image Fusion Parameter

The Mutual information (MI), the objective image fusion performance metric ($Q^{AB/F}$), spatial frequency (SF) and entropy are important image fusion parameters to evaluate quality of fused image when reference image is not available. MI described (Xydeas, 2000) can also be used without the reference image by computing the MI between reference image IA, IB and fused image IFUSE. MI between image IA and IFUSE called as I_{AF} and similarly compute I_{BF} between image IB and IFUSE. Total MI is computed as described by (7)

$$MI = I_{AF} + I_{BF} \tag{7}$$

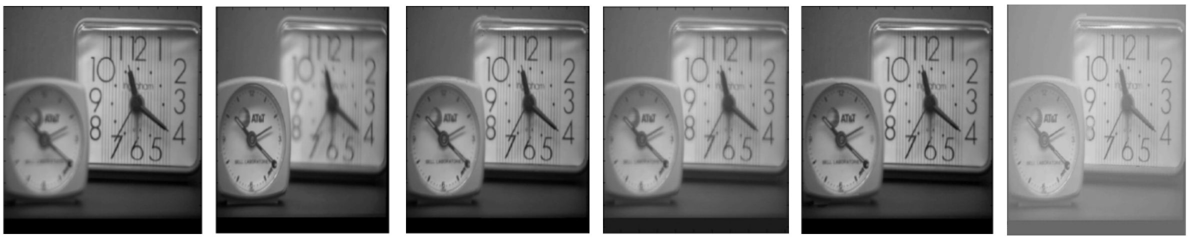
The objective image fusion performance metric $Q^{AB/F}$ which is proposed by Xydeas and Petrovic (Xydeas, 2000) reflects the quality of visual information obtained from the fusion of input images and can be used to compare the performance of different image fusion algorithms. The range of $Q^{AB/F}$ is between 0 and 1. The value 0 means all information is lost and 1 means all information is preserved.

4 SIMULATION RESULTS

The novel region based image fusion algorithm as described in section 2 has been implemented using Matlab 7. The proposed algorithm is 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 (Millimetre Wave) images. The large image dataset is required to verify the robustness of an algorithm. The simulation results are shown in Fig. 4 to 8. Proposed algorithm is applied on various categories of images for different segmentation levels and after analyzing the results, we have considered nine segmentation levels for all our experiments which improve visual quality of final fused image. The performance of proposed algorithm is evaluated using standard reference based and nonreference based image fusion evaluation parameters explained in previous section.

4.1 Fusion Results 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. 4 (a) & (b) clock image, Fig. 5 (a) & (b) pepsi image, Fig. 6 (a) & (b) book image and Fig. 7 (a) &

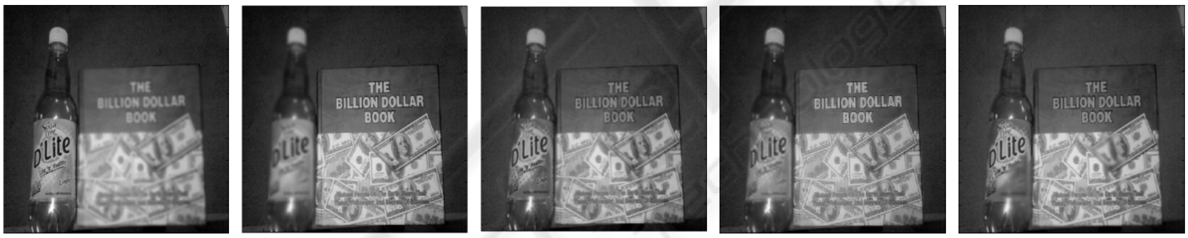


(a) (b) (c) (d) (e) (f)

Figure 4: Fusion results of multi-focus clock image (a), (b) Multi-focus source images (c) Proposed method (d) DWT & (e) Li’s method (f) Without region consistancy rule.

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

Figure 5:Fusion results of multi-focus pepsi image (a), (b) Multi-focus source images (c)Proposed method (d)DWT & (e) Li’s method.



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

Figure 6:Fusion results of multi-focus book image (a), (b) Multi-focus source images (c) Proposed method (d) DWT & (e) Li’s method.

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

Figure 7:Fusion results of multi-focus text image (a), (b) Multi-focus source images (c) Proposed method (d) DWT & (e) Li’s method.

(b) text images respectively. In Fig. 4 to 7 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 (Anna, 2006) and region based fusion method proposed by Li and Yang (Shutao, 2008).

The visual quality of the resultant fused image of proposed algorithm is better than the fused image obtained by other reported methods. The reference based and non reference based image fusion

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

Figure 8 Fusion results for multimodality IR image (a) visible image (b)IR source image (c)Proposed method (d) DWT & (e) Li's method.

Table 1: Ref. based image fusion parameters.

Image	Fusion Methods	Fusion Parameters			
		SF	*MIr*	*RMSE*	*SSIM*
Text image	DWT Based	8.1956	1.5819	6.3682	0.9259
	Li's Method	10.405	1.4713	5.2671	0.9749
	Proposed Method	10.736	1.9997	2.8313	0.9904
Book Image	DWT Based	12.865	3.8095	7.5994	0.9274
	Li's Method	16.416	3.6379	5.0847	0.9782
	Proposed Method	17.415	6.5173	1.6120	0.9974

parameter comparisons are depicted in Table 1 and Table 2. All reference based image fusion parameters SF, MIr, RMSE and SSIM are significantly better for proposed algorithm compared to other methods as depicted in Table 1. Also non reference based image fusion parameters as depicted in Table 2 are better than compared methods. In Table 2, SF and $Q^{AB/F}$ are remarkably better than other compared fusion methods which is also evident from the visual quality of resultant fused image.

Table 2: Non Ref. Based Image Fusion Parameters.

Image	Fusion Methods	Fusion Parameters			
		SF	*MI*	*$Q^{AB/F}$*	*Entropy*
Clock image	DWT Based	8.1501	5.848	0.5696	8.1506
	Li's Method	10.113	7.356	0.7156	8.7803
	Proposed Method	10.8792	7.713	0.6850	8.7813
Pepsi image	DWT Based	11.6721	2.521	0.9287	8.7293
	Li's Method	13.532	2.703	0.9683	7.1235
	Proposed Method	13.648	5.863	0.7857	7.2350

4.2 Fusion of Multimodality Images

The effectiveness of the proposed algorithm can be proved by extending its application to the multimodality concealed weapon detection (MMW images) and IR images. MMW camera image with the gun is shown in Fig. 9 (a) and visible images of a group of persons are shown in Fig. 9 (b). 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. 8 (a) and IR camera detect the human in captured image as shown in Fig. 8 (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 generated by applying proposed method is better than other reported methods. New MMS fusion rule is used in proposed algorithm. This rule preserves critical regions in fused image which is also evident in Table 3. The entropy is significantly better than region based methods as depicted in Table 3. Entropy is considered to evaluate the final fusion results of both IR and MMW multimodality source images because in both the cases IR and MMW sensor source images are blurred however in that case SF and $Q^{AB/F}$ do not give significant values for comparison. The simulated results depicted in Table 1, 2 and 3 show that proposed method performs better than other compared methods for broad categories of multifocus and multimodality images.

Table 3: Fusion Parameter for Multisensor Images.

Image	Fusion Method	Entropy
IR Image	DWT Based	6.6842
	Li's Method	6.0472
	Proposed Method	6.7814
MMW Image	DWT Based	4.9802
	Li's Method	3.7593
	Proposed Method	6.9502

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

Figure 9: Fusion results for multimodality MMW image(a)visual image(b)MMW image(c)Proposed method (d) DWT & (e) Li's method.

5 CONCLUSIONS

In this paper, new region based image fusion method using region consistency rule is described. This novel idea is applied on large number of dataset of various categories and simulation results are found with superior visual quality compared to other earlier reported pixel and recently proposed Li's region based image fusion methods. The novel MMS fusion rule is introduced to select desired regions from multimodality images. Proposed algorithm is compared with standard reference based and nonreference based image fusion parameters and from simulation and results, it is evident that our proposed algorithm preserves more details in fused image. Proposed algorithm can be further improved by designing more complex fusion rule.

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