

A Novel Multimodality Image Fusion Method Using Region Consistency Rule

Tanish Zaveri¹ and Mukesh Zaveri²

¹ EC Department, Nirma University, Ahmedabad, India
ztanish@nirmauni.ac.in

² Computer Engineering Department,
Sardar Vallabhbhai National Institute of Technology Surat, India
mazaveri@coed.svnit.ac.in

Abstract. This paper proposes an efficient region based image fusion scheme using discrete wavelet transform. This paper also proposes two new fusion rules namely mean, max and standard deviation (MMS) and region consistency rule. The proposed algorithm identifies the given images are multisensor or multifocus automatically. It allows best suitable algorithm for segmenting the input source 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 is evident from simulation results of our proposed algorithm that it preserves more information compared to earlier reported pixel based and region based methods.

1 Introduction

In recent years, image fusion algorithms are used as effective tools in medical image processing, remote sensing, industrial automation, surveillance and defense applications. Due to these broad areas of applications, image fusion has emerged as a promising and important research area in recent years. The information coming from different sensors like optical cameras, millimeter wave cameras, Infrared cameras, x-ray cameras and radar cameras are required to fuse to increase amount of information in final fused image.

There are various techniques for image fusion at pixel level is available in literature [1] [2] [3]. In the recent literature [4], simulation results of region based image fusion method show better performance than pixel based image fusion method. 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 [3]. Recently researchers also recognized that it is more meaningful to combine objects or regions rather than pixels. Piella [3] also proposed a multiresolution region based fusion scheme using link pyramid approach. The proposed method provides automatic and powerful framework for region based image fusion method which produces good quality fused image for different categories of images.

2 Proposed Algorithm

Most image fusion methods are static and semiautomatic as they do not change and adapt different fusion rules automatically as kind of input source image changes so it is difficult to generate good quality fused image using single algorithm designed for one kind of images. The block diagram of proposed method is shown in Fig. 1. Image identification (Id) block shown in block diagram are used to identify the category of source images which may be multifocus and multimodality source images.

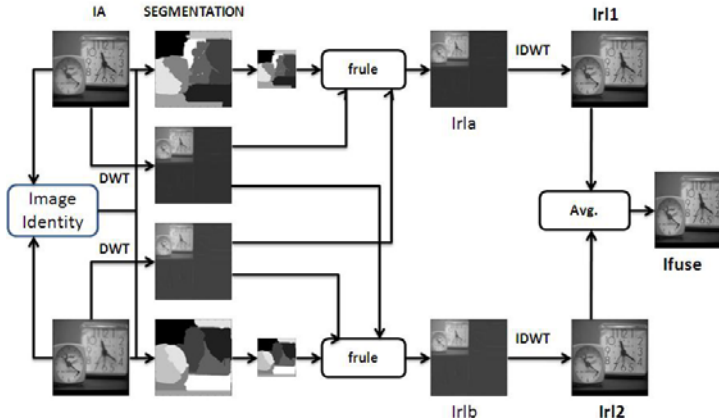


Fig. 1. Block Diagram of Proposed Method

Multifocus images are taken from the same camera but with the different focus points so it is expected that pixel intensity values between two source images do not change significantly. While in multisensor images are taken from the different sensor cameras so more difference in pixel intensity value will be expected between two source images which leads to more difference in value of MMS between two source images. The MMS value is significantly higher in case of multisensor images compared to multifocus images. The image identification (Id) is computed as described in equation (1).

$$Id = |Me1 - Me2| + |Std1 - Std2| + |MMS1 - MMS2| \quad (1)$$

Where Me1, Me2, Std1, Std2, MMS1 and MMS2 are mean, standard deviation and mean max and standard deviation parameter of source image IA and IB respectively. MMS parameter is described in detail later in this section and it is computed using eq. (3). If $Id \geq \text{threshold}$ than input source image is considered as multisensor source image. The details of threshold described in next section.

In the proposed algorithm DWT is used to decompose the input source images and inverse DWT is used to generate final fused image. The decomposed images arise from separable applications of vertical and horizontal filter. The resultant first level four image includes LL_1 sub band image corresponds to coarse

level approximation image and other three image includes (LH_1, HL_1, HH_1) sub band images corresponds to finest scale wavelet coefficient detail images. Most image fusion method [1] based on DWT is applying max or average fusion rule on DWT decomposed approximate and detailed images to generate final fused image. This fusion rule based on DWT introduces undesired information in final fusion image. To remove this undesired information consistency rule is used which described later in this section. The following the steps are used to generate final fused image after image identification step.

Step 1. The DWT 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. If $Id \leq t_h$ than normalized cut segmentation algorithm is applied on image IA otherwise k-means algorithm is used as segmentation algorithm. Segmented image is then down sampled to match the size of DWT decomposed image.

Step 3. Then n numbers of segmented regions are extracted from approximate component of image IA and IB using segmented image. 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 to measure the overall clarity of an image or region. The spatial frequency of that region is calculated using Row frequency (RF) and Column frequency (CF) as described in [4]. First fusion rule is region based spatial frequency (SF) rule as described in [4] is used to identify more informative region extracted from multifocus source images and image I_{r1a1} is generated. SF of nth region of Image IA and IB is defined as SF_{An} and SF_{Bn} respectively.

$$I_{r1a1} = \begin{cases} RA_{An} & \text{if } SF_{An} \geq SF_{Bn} \\ RA_{Bn} & \text{if } SF_{An} \leq SF_{Bn} \end{cases} \quad (2)$$

Here n is a number of regions and it varies from 1 to i. where $n = 1, 2, \dots, i$. Regions extracted after applying normalized cut set segmentation algorithm on approximate image (LL_{1A}) are represented as RA_{An} and RA_{Bn} respectively. I_{r1a1} 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 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

$$MMS_{An} = ME_{An}/SD_{An} * R_{Anmax} \quad (3)$$

Where ME, SD and R_{max} are mean, standard deviation and maximum intensity value of nth region of source image respectively. The MMS is computationally efficient and effective. 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 and IR have ME value high and SD is low so in our algorithm we have used both SD

and ME with maximum intensity value 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

$$I_{ral1} = \begin{cases} RA_{An} & \text{if } MMS_{An} \leq MMS_{Bn} \\ RA_{Bn} & \text{if } MMS_{An} \geq MMS_{Bn} \end{cases} \quad (4)$$

Intermediate fused image I_{ral1} is generated by fusion rule 2 which is applied for multimodality images and first fusion rule is applied for multifocus 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 (5). Region consistency rule states that analyze the results of fusion rule 1 or 2 of approximate component and select corresponding nth region of detail component as described below.

$$I_{rlv1} = \begin{cases} RD_{An} & \text{if } I_{rla1} = RA_{An} \\ RD_{Bn} & \text{if } I_{rla1} = RA_{Bn} \end{cases} \quad (5)$$

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. After applying fusion rule 1, approximate component of nth region is selected from image IA than corresponding detail component nth regions also selected from the same image IA to generate final fused image.

Step 4. Then 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.

These 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. In the next section image fusion evaluation criteria is described in brief.

3 Simulation Results

Image fusion performance evaluation parameters are divided into two categories reference based and non reference based which is described in [7].The proposed algorithm has been implemented using Matlab 7. The proposed algorithm applied on 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 multisensor IR (Infrared) images. The simulation results are shown in Fig. 2 and 3. Threshold value of image identification (Id) of source image is considered as 10. This value is used to differentiate between category of multimodality or multisensor image. This value is decided



Fig. 2. Fusion Results of Multifocus Book Image (a),(b) Source Images (c) Proposed Method (d) Li's Method [4] (e) DWT based method [1]

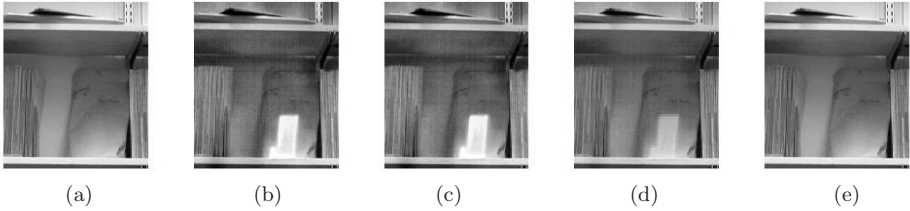


Fig. 3. Fusion Results of Multisensor Gun Image (a) Visual Image (b) IR image (c) Proposed Method (d) Li's Method [4] (e) DWT based method [1]

Table 1. Image Fusion Parameters for Multifocus Images

Image	Fusion Methods	Fusion Parameters			
		SF	Mir	RMSE	SSIM
Text Image	DWT Based [1]	8.1956	1.5819	6.3682	0.9259
	Li's Method [4]	10.405	1.4713	5.2671	0.97499
	Proposed Method	10.736	1.9997	2.8313	0.9904
Book Image	DWT Based [1]	12.865	3.809	7.599	0.927
	Li's Method [4]	16.416	3.637	5.084	0.978
	Proposed Method	17.415	6.517	1.612	0.997

Table 2. Image Fusion Parameters for Multisensor Images

Image	Fusion Methods	Entropy	MI
IR Image	DWT Based [1]	6.654	1.329
	Li's Method [4]	6.740	4.782
	Proposed Method	6.781	4.812
Book Image	DWT Based [1]	7.412	4.569
	Li's Method [4]	7.372	7.152
	Proposed Method	7.535	7.176

after many experiments on different category of images. Proposed algorithm is applied on various categories of images for different segmentation levels and after analyzing those results, we have considered nine segmentation levels for all our experiments which improve visual quality of final fused image. The performance of proposed algorithm evaluated using standard reference based and nonreference based image fusion evaluation parameters which are depicted in Table 1 and Table 2. The visual quality of the resultant fused image of proposed algorithm is better than the fused image obtained by other compared methods.

4 Conclusion

In this paper, new automatic DWT and region based image fusion method using region consistency rule is implemented. The proposed algorithm identifies the type of images that is a given set of images for fusion is multisensor or multifocus images. The proposed algorithm is applied on large number of dataset of various categories of multifocus and multisensor images. It has been observed that visual quality of proposed algorithm is better compared to other earlier reported pixel and region based image fusion method. The novel MMS fusion rule is introduced to select desired regions from multimodality images. Proposed algorithm also compared with standard reference based and nonreference based image fusion parameters and from simulation and results, it is found that visual quality and assessment parameters are better than other earlier reported methods.

References

- [1] Anna, W., Jaijining, S., Yueyang, G.: The application to wavelet transform to multimodality medical image fusion. In: IEEE International Conference on Networking, Sensing and Control, pp. 270–274 (2006)
- [2] Miao, Q., Wang, B.: A novel image fusion method using contourlet transform. In: International Conference on Communications, Circuits and Systems Proceedings, vol. 1, pp. 548–552 (2006)
- [3] Piella, G.: A general framework for multiresolution image fusion: from pixels to regions. *Journal of Information Fusion* 4(4), 259–280 (2003)
- [4] Shutao, L., Bin, Y.: Multifocus image fusion using region segmentation and spatial frequency. *Image and Vision Computing* 26, 971–979 (2008)
- [5] Shi, J., Malik, J.: Normalized cuts and image segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence* 22(8), 888–905 (2000)
- [6] Zheng, L., Robert, L.: On the use of phase congruency to evaluate image similarity. In: IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP, vol. 2, pp. 937–940 (2006)
- [7] Tanish, Z., Mukesh, Z.: Region Based Image Fusion for detection of Ewing Sarcoma. In: Seventh International conference on Advances in Pattern Recognition, pp. 240–242 (2009)