

Novel Hybrid Multispectral Image Fusion Method using Fuzzy Logic

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Abstract

In recent years, multispectral image fusion methods are viewed as an effective tool to analyze multiband remote sensing images. In this paper a novel hybrid multispectral image fusion method using combine framework of wavelet transform and fuzzy logic is proposed. The proposed method provides novel tradeoff solution between the spectral and spatial fidelity and preserves more detail spectral and spatial information. New hybrid image fusion rules are also proposed. Proposed method is applied on registered Panchromatic and Multispectral images and simulation results are compared with standard image fusion parameters. The simulation results of proposed method also compared with five different standard Pan sharpening methods available in literature. It has been observed from simulation results that proposed algorithm preserves better spatial and spectral information and better visual quality compared to earlier reported methods.

Keywords: Fusion, Multispectral, Discrete Wavelet Transform, Fuzzy logic

1. Introduction

In recent years the application of multispectral (MS) image fusion algorithm in remote sensing area has drawn the attention of researchers due to increasing availability of Earth satellites. The synthesis of multispectral image to the higher spatial resolution of the Panchromatic (Pan) image is called as Pan sharpening method but standard Pan sharpening methods do not allow control of the spatial and spectral quality of the fused image [1]. Also, the color distortion is the most significant problem in standard pan-sharpening methods. Though the aim of multispectral fusion method is same as Pan sharpening method, the approach used in both methods to reduce distortion is fundamentally different.

According to Piella [2], fusion process is nothing but a combination of salient information in order to synthesize an image with more information than individual image and synthesized image is more suitable for visual perception. This process leads to more accurate data interpretation and utility. Pan sharpened multispectral

image is a fusion product in which the MS bands are sharpened by the higher-resolution Pan image. In this paper, we focus on color distortion problem which is produced due to multispectral image fusion process. The resultant fused image can be used for Classification or image analysis which is an important research area of remote sensing. Most earth resource satellites, such as SPOT, IRS, Landsat 7, IKONOS, QuickBird and OrbView, plus some modern airborne sensors, such as Leica ADS40, provide both Pan images at a higher spatial resolution and MS images at a lower spatial resolution [1]. We assume that Pan and MS input data sets are a priori geometrically registered.

Various pan sharpening methods have been developed earlier; the comprehensive review of most published image fusion techniques is described by Pohl and Van Genderen [3]. Most successful pan sharpening methods are in general fall into the following three categories: (1) projection and substitution methods, such as Intensity Hue Saturation (IHS) fusion, and Principal Component Analysis (PCA) fusion; [3][4][6] (2) band ratio and arithmetic combination, such as Brovey transform (BT) and SVR (Synthetic Variable Ratio), and (3) the recently popular wavelet transform and contourlet transform based fusion which injects spatial features from panchromatic images into multispectral images [5][8][9][10]. All the three IHS method, PCA method and BT based methods are most popular and standard algorithms among remote sensing community due its advantages and practical applications.

Many research papers have reported the limitations of existing fusion techniques [3][4][5][6][7]. Due to the Pan sharpening process color distortion is appeared in resultant image which can be reduced using different strategies available in literature [1][8]. Each method is solution for kind of image dataset. However, the color distortion problem appears significantly in these techniques which leads to poor spectral fidelity in all these three methods compared to recently proposed multiscale transform with multiresolution decomposition based approach. No satisfactory solution has been achieved which can consistently produce high quality fusion for different data sets as well as reduce color distortion.

To overcome these limitations, in this paper a hybrid multispectral image fusion algorithm based fuzzy logic and wavelet transform is proposed. The paper is organized as follow; the proposed method is described in section 2. The evaluation parameters of multispectral image fusion methods are described in section 3. The simulation results of proposed algorithm are assessed and compared with five different standard methods available in literature which is described in section 4. It is followed by conclusion.

2. Proposed Method

The proposed method provides a novel framework which gives tradeoff solution to get better spectral and spatial quality fused image. The block diagram of proposed method is shown in Fig. 1, Fig. 2 and Fig. 3. Both MS and Pan images are considered as input source image. The IHS color space is used to apply proposed algorithm because of its less computational complexity and more practical applications. The Simple IHS method described in [3] is standard Pan sharpening method which produces color distortion because in that method only Pan image is used to modified intensity image which may produced good spatial quality Pan sharpened image but less amount of spectral quality can be preserved in it. In the proposed method, to increase spectral component while preserving spatial details both input intensity images are considered to produce modified Pan intensity image Imatch. The proposed algorithm steps to generate the fused image are described below and block diagram is also shown in Fig. 1, Fig. 2 & Fig. 3.

- (1) Consider Pan and MS images as input source images and perform RGB to HSI operation as described in [11] to extract intensity components of both the images, Ip and Im.
- (2) Perform Match Measure operation [12] between Ip and Im to obtain the Imatch image.

- (3) Take pixel-based average between Ip and Imatch to obtain I1 and between Im and Imatch to obtain I2.
- (4) Perform region based segmentation [8] with n regions on Imatch to obtain n segments.
- (5) These segments are superimposed on I1 and I2 and their corresponding regions are compared based on the parameters – Average Gradient and Standard Deviation, giving two images I_AG and I_SD by replacement. The fusion rule for each segment is given as

$$I_AG = \begin{cases} I1_n & I1_{AG_n} \geq I2_{AG_n} \\ I2_n & I1_{AG_n} < I2_{AG_n} \end{cases} \quad (1)$$

where comparison is on the basis of average gradient (AG) of the nth corresponding segment of I1 and I2 respectively for the I_AG image. Similarly for I_SD image, the comparison is on the basis of standard deviation (SD).

$$I_SD = \begin{cases} I1_n & I1_{SD_n} \geq I2_{SD_n} \\ I2_n & I1_{SD_n} < I2_{SD_n} \end{cases} \quad (2)$$

- (6) I_AG and I_SD are averaged separately with Ip which yields the average gradient image and standard deviation image.
- (7) Consider Imatch and Im images. Apply discrete wavelet transform on each of them to obtain approximation and detail components for each represented as $I_{ACT,j,k}$ and $I_{DCT,j,k}$ respectively. Here j represents decomposition level of wavelet transform and k represents the band of multispectral source image.
- (8) Consider detail components $I_{DCT,j,k}$ of Imatch and Im. Energy is a parameter used to measure texture uniformity and activity level in an image. The energy is computed for window size (M x N) as

$$E_{n,j,k}^d = \sum_{x=1}^M \sum_{y=1}^N [I_{n,DCT,j,k}^d(x,y)]^2 \quad (3)$$

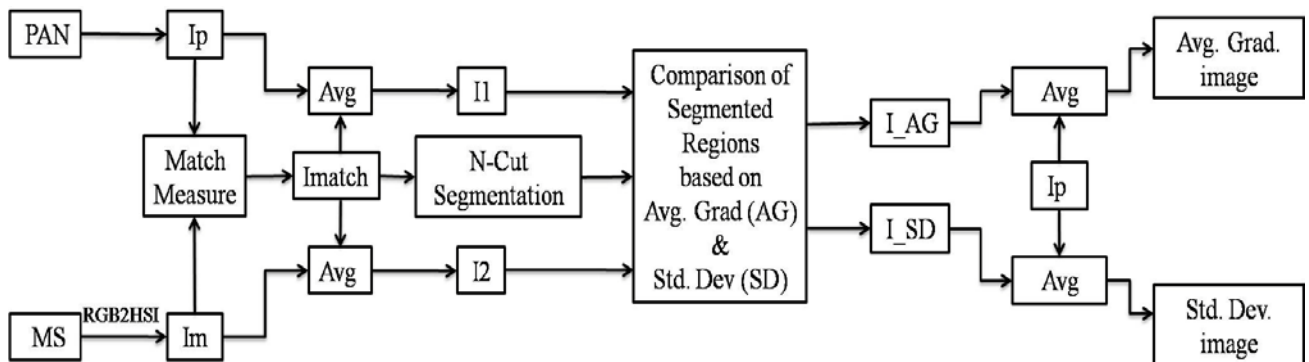


Fig.1. Proposed Method - Obtaining Average Gradient Image and Standard Deviation Image

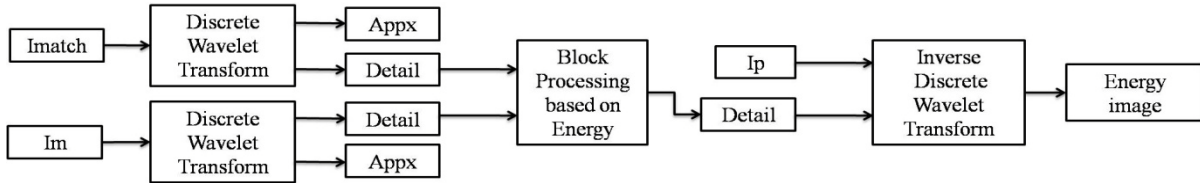


Fig.2. Proposed Method – Obtaining Energy Image

The fusion rule defined here is block processing based energy max rule for window size (M x N). It can also be called as directive energy fusion rules. The block of pixels whose directive energy are maximum are saved to be the pixels of the fused image.

$$I_{FE,j,k}^d = \begin{cases} I_n^{dDWT,j,k} & \text{if } E_{n,j,k}^d \geq E_{m,j,k}^d \\ I_m^{dDWT,j,k} & \text{if } E_{n,j,k}^d < E_{m,j,k}^d \end{cases} \quad (4)$$

(9) Inverse wavelet transform is applied on the detail components obtained in the above step and Ip is considered to be the approximation component for reconstruction. Thus a modified Energy image is obtained.

(10) Applying Fuzzy logic based fusion on the three modified images – Energy image, Average gradient image and Standard deviation image.

(11) Finally, the H and S components of MS image is combined with the I_fused intensity image to obtain the final fused RGB image.

The Mamdani fuzzy model is implemented in MATLAB based Fuzzy Inference System (FIS). The priority assigned to the parameters in order is standard deviation, average gradient and energy respectively. 3 Gaussian functions representing low, medium and high values are used as input and output membership functions as shown in Fig. 4. The variance for every gaussian function is kept constant. The AND (min) logic is used for calculating the output weights. Defuzzification is

carried out using three different methods – Centroid, MoM (Mean of Maximum) and Bisector [13].

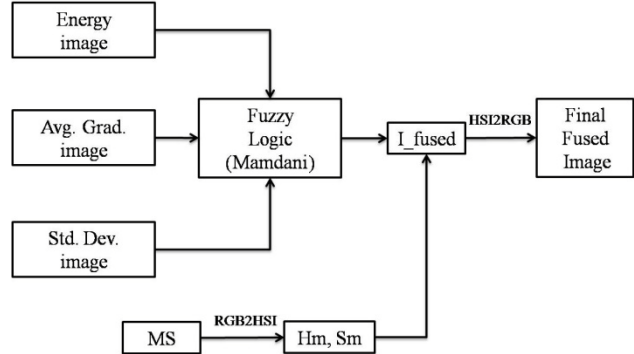


Fig. 3. Proposed Method – Fusion of Energy Image, Average Gradient Image and Standard Deviation Image using fuzzy logic

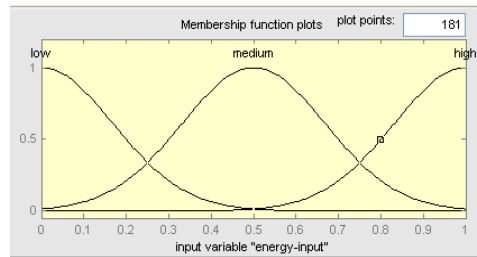


Fig. 4. Input variables as Gaussian functions for low, medium and high values.

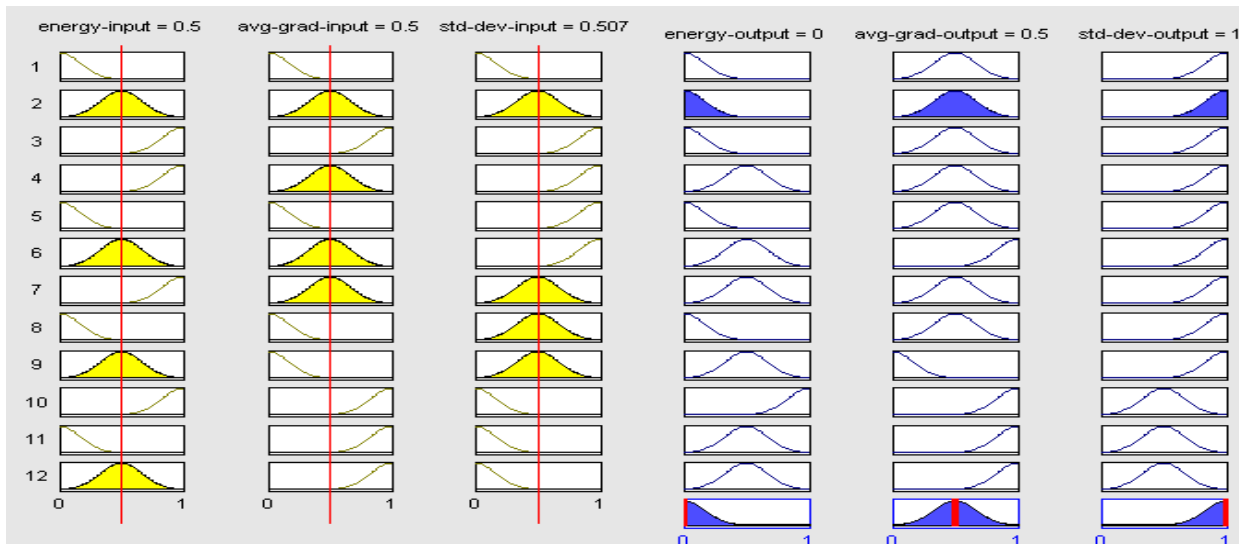


Fig. 5. The Rule Viewer

The rules are as follows:

R1: IF Energy is Low and Standard Deviation is Low and Average Gradient is Low THEN Energy is Low and Standard Deviation is Medium and Average Gradient is High.

R2: IF Energy is Medium and Standard Deviation is Medium and Average Gradient is Medium THEN Energy is Low and Standard Deviation is Medium and Average Gradient is High.

R3: IF Energy is High and Standard Deviation is High and Average Gradient is High THEN Energy is Low and Standard Deviation is Medium and Average Gradient is High.

R4: IF Energy is High and Standard Deviation is Medium and Average Gradient is High THEN Energy is Medium and Standard Deviation is Medium and Average Gradient is High.

R5: IF Energy is Low and Standard Deviation is Low and Average Gradient is High THEN Energy is Low and Standard Deviation is Medium and Average Gradient is High.

R6: IF Energy is Medium and Standard Deviation is Medium and Average Gradient is High THEN Energy is Medium and Standard Deviation is High and Average Gradient is High.

R7: IF Energy is High and Standard Deviation is Medium and Average Gradient is Medium THEN Energy is Medium and Standard Deviation is Medium and Average Gradient is High.

R8: IF Energy is Low and Standard Deviation is Low and Average Gradient is Medium THEN Energy is Low and Standard Deviation is Medium and Average Gradient is High.

R9: IF Energy is Medium and Standard Deviation is Low and Average Gradient is Medium THEN Energy is Medium and Standard Deviation is Low and Average Gradient is High.

R10: IF Energy is High and Standard Deviation is High and Average Gradient is Low THEN Energy is High and Standard Deviation is High and Average Gradient is Medium.

R11: IF Energy is Low and Standard Deviation is High and Average Gradient is Low THEN Energy is Medium and Standard Deviation is High and Average Gradient is

Medium.

R12: IF Energy is Medium and Standard Deviation is High and Average Gradient is Low THEN Energy is Medium and Standard Deviation is High and Average Gradient is Medium.

Thus, three important activity level measurement feature parameters are considered to compare the details from both source images. After designing the rules, the impact of input variables on the output variables, is observed in case of each rule, in the rule viewer for MATLAB based fuzzy inference systems as shown in Fig. 5. Similarly the surfaces for different combinations of input variables and output variables are shown in Fig. 6.

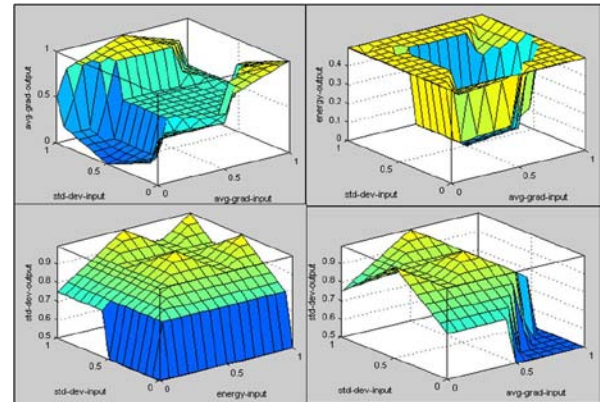


Fig. 6. Surfaces for the fuzzy rules for different input and output variables for MoM defuzzification method.

3. Evaluation Criteria

There are many different performance evaluation indices are available in literature [3][4][5][11] to analyze Pan sharpened images. These indices are divided into mainly three categories which include spatial quality indices, spectral quality and average indices to analyze the effect of both simultaneously. There are many parameters are available to judge spatial quality of Pan sharpened image like Cross correlation (CC), distortion extent (DE), Root mean square error (RMSE) or Universal image quality (UQI) indices explained in [3][11]. Even by analyzing visual quality of an image it is easy to analyze the sharpness of the edges or spatial quality of an image but it is much more difficult to match

Table I. Results for UNB image

<i>Image : UNB</i>	Spectral					Spatial		Common
Methods	SNR	CC	DE	ERGAS	RASE	SNR	CC	Avg.CC
I.H.S. [3]	53.8472	0.4951	48.0945	14.6868	72.6107	58.7294	0.9542	0.7247
I.H.S.-MI [11]	54.0013	0.5182	47.5543	12.9587	72.9328	60.1452	0.9671	0.7426
PCA [14]	54.0404	0.5224	47.5914	12.4869	72.7675	62.2889	0.9884	0.7554
WT [12]	53.6414	0.8113	52.7333	30.7221	61.4662	55.4462	0.6944	0.7529
Brovay [11]	54.6283	0.6112	40.7145	12.2871	63.6670	59.6845	0.9616	0.7864
Proposed Method	56.1263	0.8385	27.5459	9.9062	47.2357	56.4684	0.8405	0.8395

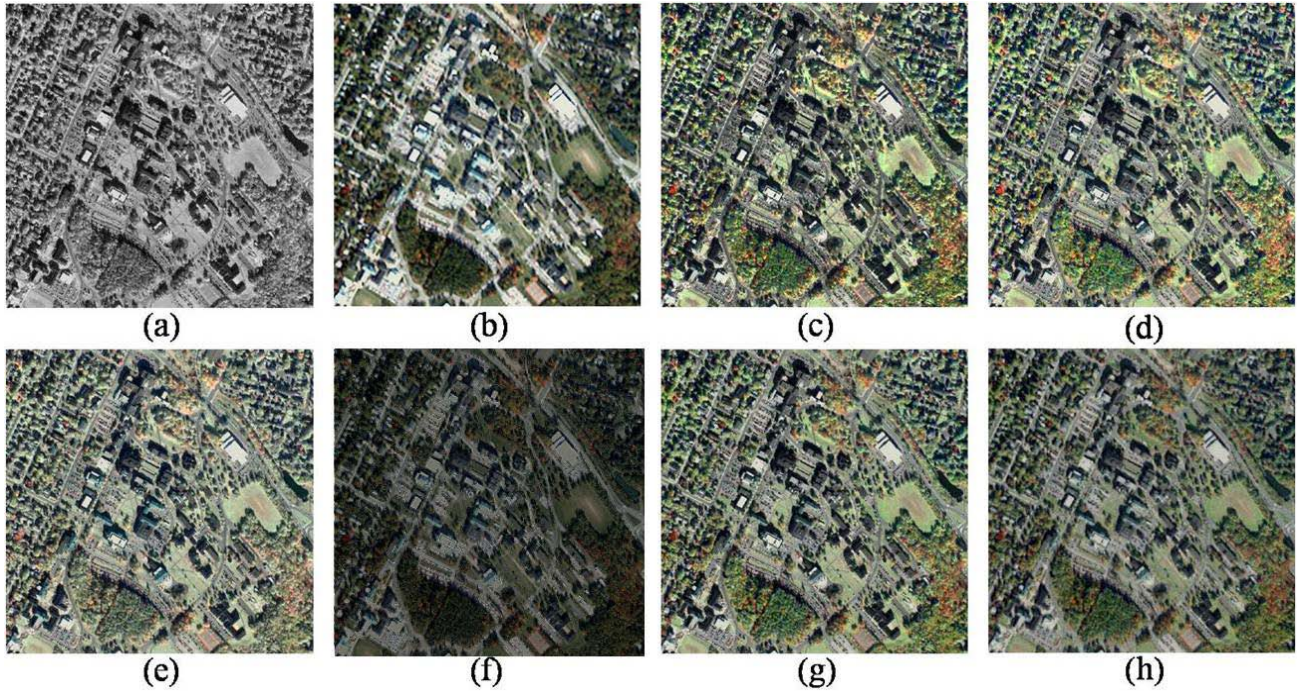


Fig. 7. Fusion Results of UNB image (a) 1m Panchromatic image (b) 4m Multispectral image (c) IHS Method (d) Modified IHS Method (e) PCA based method (f) WT based method (g) Brovey Transform Method (h) Proposed Method



Fig. 8. Fusion Results of IKONOS-2 image (a) 1m Panchromatic image (b) 4m Multispectral image (c) IHS Method (d) Modified IHS Method (e) PCA based method (f) WT based method (g) Brovey Transform Method (h) Proposed Method

the colors of the final result to the original multispectral images.

There are many indices [3][11] that analyze the spectral quality of final fused image like Relative global error in synthesis (ERGAS), Spectral angle mapper

(SAM), Relative average spectral error (RASE). The Cross correlation (CC) and Signal to noise ratio (SNR) [12] can be used to analyze both quality factors. All these parameters are explained in literature [3][14].

Table II. Results for IKONOS-2 image

IKONOS-2 Methods	Spectral					Spatial		Common
	SNR	CC	DE	ERGAS	RASE	SNR	CC	Avg.CC
I.H.S. [3]	52.7779	0.2913	40.5614	15.2827	61.1364	56.6429	0.9215	0.6064
I.H.S.-MI [11]	52.6654	0.3461	45.2785	12.3989	62.8061	60.7905	0.9692	0.6577
PCA [14]	52.4540	0.3626	48.5633	12.1684	65.7607	63.6837	0.9882	0.6754
WT [12]	53.0087	0.8803	44.8705	28.9576	57.9213	52.9568	0.4547	0.6675
Brovey [11]	53.1241	0.4404	41.5792	11.3378	56.4814	60.6501	0.9607	0.7005
Proposed Method	55.1684	0.7303	25.5593	8.3983	35.2730	56.8005	0.8444	0.7873

4. Simulation Results

The proposed algorithm has been implemented using Matlab 7. The test dataset images are downloaded from [15]. The 1m Panchromatic image and 4m multispectral image (UNB) of the city of Fredericton, Canada are shown in Fig. 7 (a) and (b) respectively. These images are acquired by the commercial satellite IKONOS. The raw multispectral image taken from the site has been resampled to the same size of the panchromatic image in order to perform registration. The other IKONOS-2 images covering an area of the city of Sherbrooke, QC, Canada, also considered as input source images as shown in Fig. 8 (a) and (b) are Pan and MS images respectively [4]. It has been observed from experiments that DWT with decomposition level 2 and normalized cut segmentation with nine segmentation regions provides better visual quality which is considered after analyzing different results of different segmentation levels at different decomposition levels. The proposed algorithm uses window size of 3 x 3. The most widely used five standard Pan sharpening methods IHS [3] and modified IHS method [11], Brovey Method [11], PCA based method [14] and wavelet transform (WT) based additive Pan sharpening method described in [12] are used to compare with simulation results of proposed method.

Average value of each quality assessment parameters of all three bands R, G and B of source images are depicted in Table I and II. It has been clearly observed from the Table I that spectral quality assessment parameters and Average cross correlation of proposed method are better than any other standard compared Pan sharpening method. It is also evident from Fig. 9 and 11. This result indicates that proposed method preserves better spectral information while losing minimum spatial information. Thus, proposed algorithm provides less color distortion compared to other compared methods. It is also observed from simulation results Table I & II that spatial parameters are better for PCA based method but it fails to preserve spectral fidelity in multispectral fused image. Multiresolution based WT method has less color distortion but spatial resolution is affected. Resultant fused images of all six methods are shown in Fig. 7 (c) to (h) and Fig. 8 (c) to (h). The variation of spectral and

spatial CC for two different set of images and for three different defuzzification methods are shown in Fig. 10 and Fig. 12. From the simulation results, it has been observed that spectral and spatial CC of MoM method is higher in UNB image and IKONOS-2 image compared to Bisector [13] and Centroid method [13]. MoM defuzzification method provides appropriate weight for proposed method. The simulation results of spectral and spatial CC of MoM based proposed method are compared with earlier reported standard five methods as shown in Fig. 10 and Fig. 12 for two different set of images.

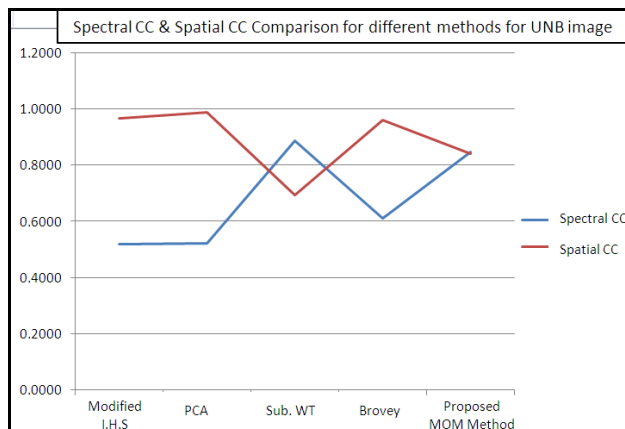


Fig. 9. Comparison of Spectral and Spatial CC for different methods for UNB image.

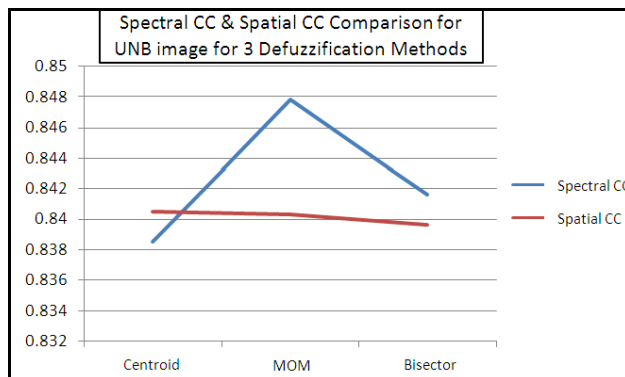


Fig.10. Comparison of Spectral and Spatial CC for Proposed Method with 3 different defuzzification methods for fused UNB image.

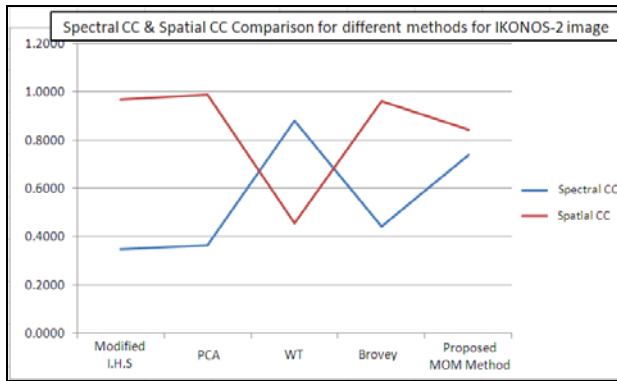


Fig. 11. Comparison of Spectral CC and Spatial CC for different methods for IKONOS-2 image.

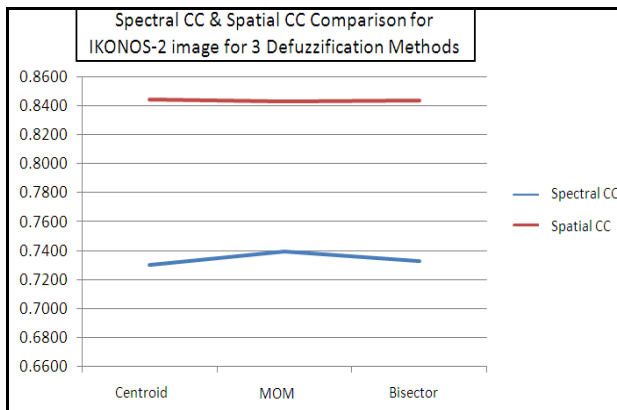


Fig. 12. Comparison of Spectral CC and Spatial CC for Proposed Method with 3 different defuzzification methods for fused IKONOS-2 image.

5. Conclusion and Further Work

There are number of applications like image classification and image analysis in remote sensing that require high spatial and spectral resolution images with minimum color distortion. The proposed hybrid image fusion method using fuzzy logic provides novel solution to minimize color distortion compared to standard Pan sharpening methods so the fused image contains more spatial and spectral details compared to earlier reported standard Pan sharpening methods. The visual quality of resultant fused image generated from proposed method is significantly better than standard methods used. More optimized and complex fuzzy rules can be designed to obtain smoother curve which can improve the quality of resultant fused image. The computational time of proposed method is higher than compared methods which can be reduced by selecting appropriate and better fusion rules. The algorithm can be further extended by incorporating neural networks for more robust fusion.

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