Asian Journal of Scientific Research

ISSN 1992-1454

OPEN ACCESS

Asian Journal of Scientific Research

ISSN 1992-1454
DOI: 10.3923/ajsr.2018.162.168

Research Article

Fusion Enhancement of Multispectral Satellite Image by Using Higher Order Statistics

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Abstract

Background and Objective: The satellite multispectral images have several bands, which have low resolution and limited information. These bands are combined into a fused single image that contains the information of all bands, but these existing fusion methods are affected by color distortion. The aim of this study was to improve the spatial and spectral information of satellite images by using higher order statistics in combination with intensity hue saturation and wavelet method. It exhibited higher performance than the color normalization and Panchromatic sharpening techniques. **Materials and Methods:** The present study developed a new fusion enhancement method for National Oceanic and Atmospheric Administration multispectral satellite images to provide an improved conceptual framework with minimal color distortion. The following parameters are used to assess the performance of the proposed fusion enhancement method: Root mean square error, correlation coefficient, structural similarity index measure, error relative global adimensionnelle de synthese and relative average spectral error. **Results:** To reduce the dimensionality of multi band satellite images independent component analysIs is employed, which uses the higher-order statistics of the data respectively and the image is fused with High resolution panchromatic satellite image. **Conclusion:** The enhanced image of proposed algorithm are compared with previous techniques and got better improvement than previous images.

Key words: Independent component analysis, intensity, hue and saturation transformation, principal component analysis, higher order statistics, wavelets

Received: July 18, 2017 Accepted: September 09, 2017 Published: March 15, 2018

Citation: T. Venkata Krishnamoorthy and G. Umamaheswara Reddy, 2018. Fusion enhancement of multispectral satellite image by using higher order statistics. Asian J. Sci. Res., 11: 162-168.

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Competing Interest: The authors have declared that no competing interest exists.

Data Availability: All relevant data are within the paper and its supporting information files.

INTRODUCTION

Multispectral (MS), hyper spectral satellite images contain numerous bands, representing different information of these images, however, these bands have low resolution and contain limited earth related information. Therefore, to obtain more earth related data, these MS images are enhanced using image processing techniques[1]. Image fusion is one of the most effective methods for enhancing the geometrical images with radiometric resolution by merging the low resolution MS channels with high resolution panchromatic (PAN) images (16-bit) to retain the spatial information[2]. PAN images have high resolution and are very informative in gray levels only. By contrast, MS data (five bands) are limited and therefore complete information of the image cannot be obtained. Such a low resolution bands are fused with PAN images for detailed information. In a PAN sharpening process, where the same scene is retained but as a high resolution image. The combination of low resolution MS images and high resolution PAN images provides the complete and necessary information of the image. Contrast enhancement is one of the most favorable techniques for improving the spatial intensity of Remote sensing images with Gaussian or near Gaussian histograms. Many PAN sharpening techniques have been used for image enhancement including spatial, spectral and radiometric resolution transformation. Ehlers fusion, subtractive and projective hyper spherical color space resolution merge tool, wavelet resolution merge and modified IHS resolution merge methods[3,4].

Principal component analysis (PCA) is the one of the most effective techniques for reducing redundant information and dimensionality in fusion methods, however both the first and second vectors of PCAs are orthogonal, the first component represents the variability of the data and its results contain most of the information and the second vector is orthogonal to the first PCA component[5]. Similarly, all the PCA components are orthogonal to each other. The PCA can simply compress the data. In satellite images, same information is repeated in different bands, however, information separation cannot be performed through principle component analysis. Therefore, higher order statistics must be used to separate the spatial information from satellite images.

MATERIALS AND METHODS

Remote-sensing satellite image data: Recently man-made satellite image data have been increasing rapidly. Various methods have been proposed for unsupervised data and radiometric transformation techniques for higher level of enhancement. Satellite image contain the information of earth surfaces. The national oceanic and atmospheric administration (NOAA) satellite receivers receive images in the form of advance very high resolution radiometer (AVHRR) data. The NOAA AVHRR MS satellite images[6] comprise five channels ranging from visible-light wavelengths to thermal infrared (IR) wavelengths with a spatial resolution of 1.09 km. Instead of small resolution by sing high resolution it covers large earth surface area Table 1 presents the availability of channel bandwidths.

Table 1: NOAA AVHRR satellite bands

Channels	Band width (μm)	Spectral band
1	0.58-0.68	Visible
2	0.725-1.10	Near IR
3a	1.68-1.64	Mid IR
3b	3.55-3.93	Thermal IR
4	10.3-11.3	Thermal IR
5	11.5-12.5	Thermal IR

AVHRR data are very useful for sea surface temperature measurement and cloud and water land border detection. These individual MS bands have coarser resolution than PAN satellite images[7].

PCA versus ICA: Principle component transformation methods have been applied to all bands for reducing image dimensionality and the generation of uncorrelated generated additional channels. In PCA, each axis is orthogonal to each other. Typically, the first principle component image contains the maximum possible variation of the original image and the second and third components are not stored in previous principle components. Uncorrelated noise present in the last principle component as well as Gaussian noises are removed through traditional second order statistics, however, high level multiplicative and impulse noise images are analyzed using higher order statistics only. Independent component analysis (ICA) is a statistical method for transforming a multidimensional random vector data into independent components. The PCA only considers second order statistics, whereas ICA is an extension of the PCA for the blind separation of independent data from their linear mixture. It is a computational method for dividing multi variate signal into additive subcomponent. The PCA involves the decomposition of the Eigen value of the data covariance matrix or singular value decomposition of the data by using second order statistics that is applicable in Gaussian distribution only.

Statistical independence is considerably stronger with the uncorrelated variables. In ICA, the independent components Y_i are uncorrelated with each other. The ICA developed using higher order derivatives or the cumulants of mixtures and depends on kurtosis and skewness. The non-negative matrix factorization (NMF) can function as ICA, it is used for the reconstruction of data as a positive summation over the basis vectors. With the help of the images separated using ICA, any image in the data set can be reconstructed particularly after blind source separation. Second order characteristics function satisfactorily only with normal Gaussian distribution, whereas, higher order statistics are useful for non-Gaussian distribution levels. ICA can separate multivariate signals into additive non Gaussian sub components.

The proposed method is based on the independent sources and non-Gaussian distributions. This non-Gaussian family of ICA algorithms is derived from the central limit theorem based on kurtosis and negentropy. The kurtosis[7] equation is represented as Eq. 1 shown as:

$$\text{Kurtosis}(k) = \frac{E[(y-\bar{y}^4)]}{(E[y-\bar{y}^2])^2} - 3 \quad (1)$$

where, $\bar{y}$ is the sample mean of y.

Kurtosis is a measure of non-Gaussianity, the kurtosis of signal 'y' is given by $y = w^T x$, where w is the weighted vector rotated around the origin. The ICA, It is an extension of the PCA for the blind separation of independent sources from their linear mixtures[8]. The axis does not need to be orthogonal like such as in PCA, it can be expressed as:

$$Y = HX$$

Where:

Y = m-dimensional random vector
X = n-dimensional random vector with independent components and
H = Unknown transformation

These fusion techniques use the IHS color transformation method because the intensity variation the red, green and blue (RGB) color model always leads to color changes. By contrast, IHS model preserves the color despite intensity variation.

Fusion techniques: Many traditional spatial convolution filters have been implemented for enhancing the information of satellite images, such as high, low and average pass filters for sharpening and blurring of MS and hyperspectral images, gradient filters for edge detection and morphological filters for surface detection and preprocessing for image segmentation. However, these standard filtering techniques could not yield sophisticated results because of the lack of high or low frequency data or the over smoothing of images. Many algorithms have been developed to produce optimized results for fusion MS images, however, optimum values were not obtained because of inherent limitations. The averaging and wavelets methods as well as and multiplicative and Brovey transforms have been proposed[9]. Brovey transform (BT) is a color normalization technique that involves a certain trade off between the spatial and spectral resolutions. Any mismatch between image color distortions is indicated. The image ratios are used for the feature extraction of satellite images, reduction of terrain illumination effects and derivation of the particular channel ratio formula. Spatial (geometric) feature analysis applies the local neighborhood operation to raster data. Several techniques such as image smoothing, low and high pass filtering, edge detection and contrast enhancement have been implemented. Windowing movement techniques used entire geometric image for raster cell calculations. Principle and independent component analysis methods are using for representing MS images with single fused image using dimensionality reduction technique[10].

In the IHS-fusion method a mismatch occurs when the PAN and MS resolution bands are dissimilar. Subsequently the spectral characteristics of the data are changed to rectify this mismatch by using this algorithm. The rapid IHS-Fusion method with higher order statistics generate a high resolution PAN channel to increase the information content of the primary data[11].

The BT is one of the most effective techniques for color image normalization and is used as the standard method for the normalization the spectral bands. However, it does not yield satisfactory results for both spatial and spectral resolution images[12]. Moreover this method was only suitable for single-sensor and single data images and not for multisensor and multitemporal fusion images.

In the present study IHS and ICA techniques were implemented to achieve optimum results with less color distortion. To avoid color distortion and non-Gaussianity problems fusion techniques with higher order statistics were implemented to reduces redundant data[13,14], analyses the non-Gaussian noises of images and separate independent data from redundant MS images. The performance parameters, namely relative average spectral error (RASE), root mean square error (RMSE), erreur relative globale adimensionnelle de synthese (ERGAS), correlation coefficient (CC), structural similarity index measure (SSIM) and Q-factor were used to compare the results of proposed algorithms with those of previous studies[15,16].

The UIQI (universal image quality index) is the measure of the second order statistics of original and processed images, the highest value of UIQI represents the highest spectral and spatial quality of fused images. Erreur Relative Globale Adimensionnelle de Synthese (ERGAS)[17] estimates the spectral quality of the MS fused image and is applied to two images with different spatial resolution:

$$\text{ERGAS} = 100\frac{h}{l}\sqrt{\frac{1}{N}\sum_{K=1}^{N}\frac{\text{RMSE}\ (B_K)^2}{\mu(k)}} \quad (2)$$

Where:
h = Spatial resolution of the fused (PAN) image
l = Spatial resolution of reference (MS) image
μ(k) = Mean radiance of the Band

The quality of the images using the mean of SSIM, the higher value of SSIM reaching to near the original image. SSIM[18] is more accurate than MSE and peak signal to noise ratio:

$$\text{SSIM} = \frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \quad (3)$$

where, c_1 and c_2 are constants.

RASE and RMSE represent the percentage and error computed between the resultant fused image and the original image. The RASE and RMSE[19] equations are represented as Eq. 4 and 5:

$$\text{RASE} = \frac{100}{M}\sqrt{\frac{1}{k}\sum_{i=1}^{k}\text{RMSE}^2(B_i)} \quad (4)$$

$$\text{RMSE} = \frac{1}{MN}\sqrt{\sum_{m=1}^{M}\sum_{n=1}^{N}(R(m,n)-F(m,n))^2} \quad (5)$$

Where:
R (m, n) = Reference image
F (m, n) = Fused image
M = Mean radiance of the K spectral bands (Bi) of the MS images

CC is the similarity metric between resultant fused and original images. At a maximum CC value = 1 both images are equal:

$$\text{CC}(A,B) = \frac{\sum_{m,n}(A_{m,n}-\bar{A})(B_{m,n}-\bar{B})}{\sqrt{\left(\sum_{m,n}(A_{m,n}-\bar{A})^2\right)\left(\sum_{m,n}(B_{m,n}-\bar{B})^2\right)}} \quad (6)$$

Proposed method: The NOAA multispectral with 1.2 km pixel resolution. Geometric corrections are required for avoiding mismatches in the dimensionality of the two satellite images. ICA exploits higher-order statistics such as fourth order cummulant (or Kurtosis), thus minimizing the mutual information of output and non-Gaussian features of the data. In this method ICA algorithm is used to separate non orthogonal objects and perform dimensional reductions for MS image.

Let us consider proposed fusion algorithm in more detail. After geometric correction the ICA algorithm is implemented for MS image and the obtained image is in IHS model. The next step is to replace the first component of MS image with PAN image and the next information of multispectral image intensity value is replaced by Histogram matched the output of PAN and ICA output image and converting the result into RGB color model using color transformation. Finally wavelet transform is applied to get better quality or resolution of an image. The main steps illustrated in Fig. 1 of proposed fusion scheme:

- Desampling and geometric correction to the MS and PAN images for avoiding mismatches in dimensions
- ICA fusion
- Converting of the obtained MS into the IHS color model
- Transforming the R, G and B bands of the multispectral image into IHS components
- Match the Histogram of PAN to Histogram of ICA
- Uncorrelate of the new MS image (Replace the "I" component with step 4 image)
- Apply color transformation technique
- Wavelet technique to obtained output

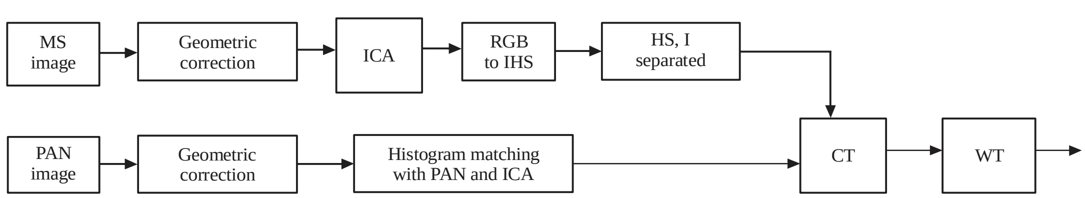

Fig. 1: Block diagram for proposed algorithm, CT: Color transform (HSV), WT: Wavelet transform and PAN: Panchromatic image

RESULTS AND DISCUSSION

In the proposed method, MS image was collected from the L-Band NOAA MS satellite receiver. The existing algorithms were verified and new enhanced fusion images were generated using a combination of ICA, IHS and wavelet transformation methods. It exhibited higher performance than some previous methods. In the present study, area of interests (AOIs) was selected from the NOAA satellite receiver[18].

Spatial domain methods are very simple and highly focused on the spatial information of input images but result in the loss of spectral information. Both spatial and spectral information are necessary for satellite data analysis[19].

Figure 2a and b represents MS and panchromatic images for NOAA satellite images. MS have combination of five low resolution bands, difficult to represent full information with low resolution, panchromatic image high resolution gray level image, Fig. 2c represents the Brovey transform image, which is performed in the RGB domain and has limited band fusion.

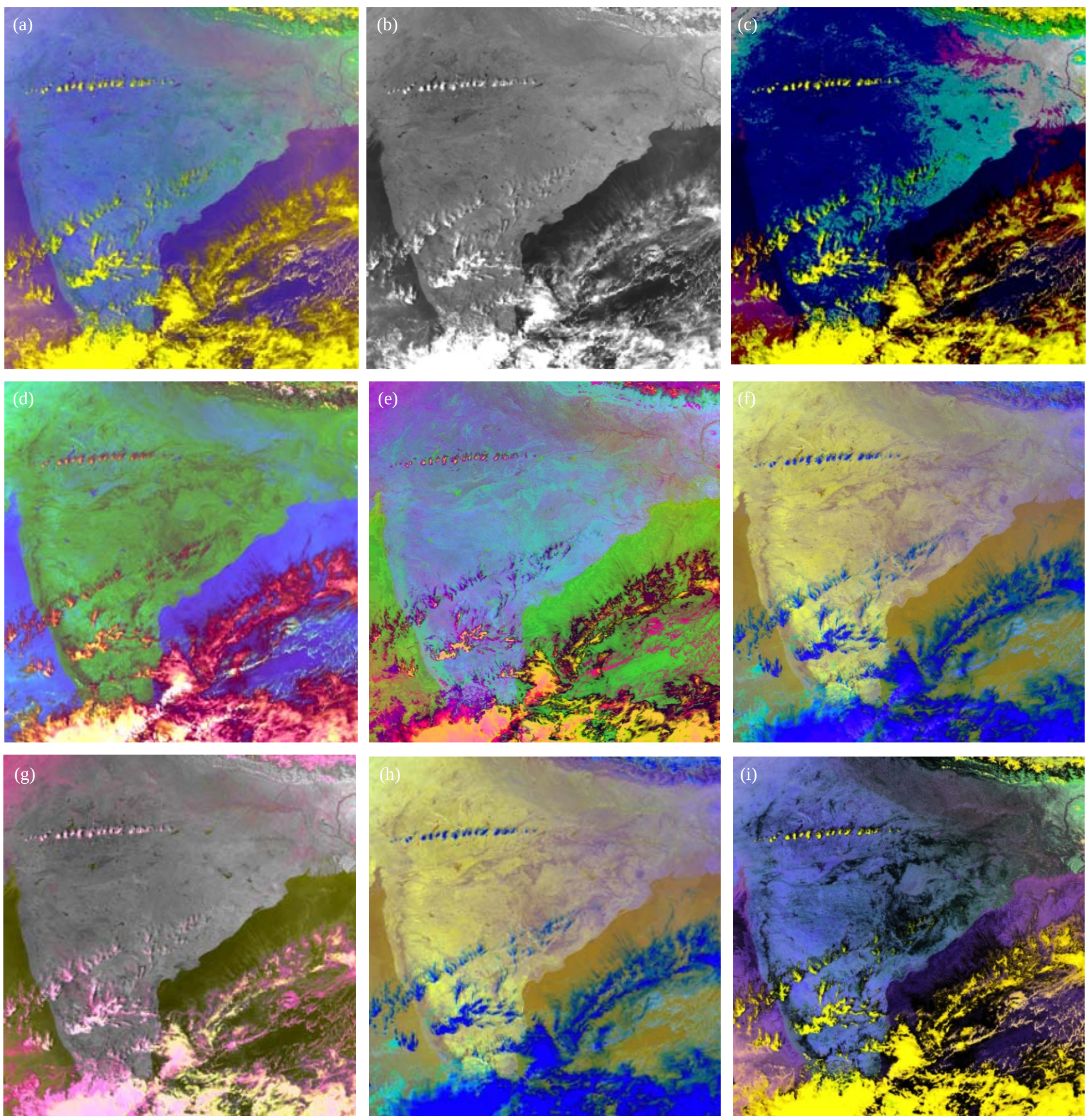

Fig. 2(a-i): (a) NOAA MSI image, (b) Panchromatic image, (c) Fused browey transform image, (d) Fused PCA image, (e) ICA image, (f) Wavelet resolution merge with PCA, (g) HIS-ICA fusion image, (h) Wavelet resolution merge image and (i) Proposed image (ICA-HSI-wavelet fusion technique)

Table 2: Comparison results of existing fusion methods with proposed method

	Original image	Wavelet resolution	Wavelet resolution (PCA). jpg	BTS	BT with ICA	IHS-ICA	ICA	PCA	Proposed method
CC	1	-0.55299	-0.49524	0.862476	0.561386	0.509177	0.390623	0.459198	0.790748
Entropy	7.57653	7.629883	7.677901	5.977368	6.699834	7.353525	7.688804	7.3258	7.70914
ERGAS	0	19.39947	19.1064	14.7188	16.22981	11.70853	11.57874	11.89501	10.49416
Q-factor	1	-0.53438	-0.48068	0.640738	0.442198	0.498302	0.389814	0.456688	0.729258
RASE	0	77.52801	76.38603	58.73459	64.9956	47.59138	46.33583	48.11303	42.01976
RMSE	0	96.38328	94.99142	72.95129	80.82211	49.1448	54.26475	54.06715	52.27446
SSIM	1	0.11144	0.11895	0.3821	0.54618	0.44961	0.37958	0.53948	0.57651

ICA: Independent component analysis, BTS: Brovey transform system, BT: Brovey transform, IHS-ICA: Intensity hue and saturation-independent component analysis, PCA: Principle component analysis

Wavelet Transform is extension of shortwave, fourier transform, total signal decomposed as Sine and Cosines but in wavelet method signal projected as wavelet functions. It gives good results in spatial and frequency domain. Wavelet resolution merged image (Fig. 2h) does not yield satisfactory results because the wavelet method unsuccessful in terms of directionality[20] and cannot capture the curves and edges. Figure 2d and f provide the output of the PCA technique[21], It is one of the most effective techniques for unlimited bands used as image classification and compression, that yields a satisfactory spatial resolution for the image but distorts the original chromocity of the input image. Therefore, the ICA techniques were used to overcome the aforementioned problems. These all fusion methods from Fig. 2c-h are comparing with spatial and spectral parameters. Table 2 presents a comparison of the different fusion techniques with the proposed method. The lower the ERGAS value, the higher the spectral quality of fused images, existing methods the parameters of spatial and spectral information entropy, CC, Q-factor and SSIM are not given sophisticated values, however, ERGAS, RASE and RMSE values were low For obtaining both spatial and spectral information.

The dimensional reduction techniques are very useful for multispectral satellite image, when using same image fused with panchromatic satellite image with IHS and wavelet method it yields optimal results compare with previous methods of NOAA MSI, Fused PCA and ICA methods.

CONCLUSION AND FUTURE RECOMMENDATIONS

The present study developed fusion enhancement techniques for MS satellite images, Windowing techniques are very useful for image enhancing and processing. The ICA is more effective than PCA for the blind separation of orthogonal data. Furthermore, ICA in combination with higher order statistics and wavelet methods considerably enhance the spatial and spectral values. The novel proposed fusion method exhibits good accuracy for both spatial and spectral resolution values.

SIGNIFICANCE STATEMENTS

In remote sensing applications, the increasing availability of space borne sensors gives a motivation for different image fusion algorithms. Several situations in image processing require high spatial and high spectral resolution in a single image. Most of the available equipment is not capable of providing such data convincingly. The proposed Image fusion techniques allow the integration of different information sources like sea images from satellite etc. The fused image can have complementary spatial and spectral resolution characteristics. However, the proposed enhancement technique is more suitable in now a day's remote sensing applications, which distort the spectral information of the multispectral data while merging.

ACKNOWLEDGMENT

Authors are grateful to the Technical Education Quality Improvement Programme, Phase II, Center of Excellence [TEQIP 1.2.1 (CoE)], Sri Venkateswara University College of Engineering, for providing research assistantship and software for this study.

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