

## Block Based Algorithm for the Fusion of Multisensor Images

<sup>1</sup>S. Naveena, <sup>1</sup>V.R.S. Mani and <sup>2</sup>S. Arivazhagan

<sup>1</sup>Department of ECE, National Engineering College, Kovilpatti, India

<sup>2</sup>Mepco Schlenk Engineering College, Sivakasi, India

**Abstract:** With the development of different types of biosensors, chemical sensors and remote sensors on board satellites, more data has become available for scientific researches. As the data volume grows, the need to combine the data gathered from different sources is increased. Multisensor image fusion is the process of combining information from two or more images of a scene into a single composite image that is more informative and suitable for computer processing. As current and future satellite systems provide both hyper spectral and multispectral images, the fusion of hyper spectral image with multispectral image results in a new image which has high spatial and spectral resolution. Thus, a block based algorithm is proposed for the fusion of hyper spectral images and multispectral images, each having different wavelength ranges. The proposed algorithm generates a simulated multispectral band using clustering technique. Then, the block association process is done by comparing the correlation between the simulated multispectral band and the hyperspectral band. Now, the high frequency information is extracted from the simulated multispectral band. This information is fused with the hyper spectral image, thus improving its spatial quality and preserving its spectral information. The performance of the proposed algorithm is evaluated using different performance measures.

**Key words:** Image Fusion • Multisensor • Hyper Spectral • Multi Spectral • Unmixing • Block based

### INTRODUCTION

Multisensor Image fusion is the process of combining relevant information from two or more images obtained using different sensors into a single image. Multisensor data often presents complementary information, so image fusion provides a resultant image that has more information than any of the input images [1]. This image has been extensively used by remote sensing community [2]. The advantages of multisensor image fusion are its extended range of operation, reduced uncertainty, increased reliability, robust system performance and its compact representation of information. Currently, lot of researches are going on in the field of multisensor image fusion. This paper presents a block based algorithm for the fusion of hyper spectral and multispectral images. Section 2 describes the traditional fusion methods. The proposed algorithm is described in section 3. The results are summarized in section 5. Finally, conclusion and future work are presented in section 6.

**Related Work:** Hyper spectral satellite images have high spectral information that helps to analyze the terrestrial features accurately. But, these images have low spatial information than panchromatic and multispectral images. Pan sharpening is the process of fusing a multispectral or hyper spectral image with a panchromatic image to generate an image with high spatial and spectral resolution [3]. Multiresolution analysis (MRA) is a pan sharpening method that is based on the injection of spatial details, which are obtained through a multiscale decomposition of the panchromatic image into the multispectral image [4]. MRA improves the spectral information of fused image, but causes spatial misalignment between the multispectral and panchromatic images. Various other methods like Component Substitution (CS) and Principal component analysis (PCA) are also available for multispectral and panchromatic image fusion [5].

Since, hyper spectral images have high benefits over the other images, hyper spectral image fusion algorithm using multispectral images has been studied. The fusion

of hyper spectral and multispectral images differs from the traditional pan sharpening methods since both of them are multi – band images containing both spectral and spatial information. Hence, the existing pan sharpening methods are inapplicable for the fusion of hyper spectral and multispectral images.

An unmixing based fusion framework using the coupled nonnegative matrix factorization (CNMF) technique was proposed to fuse the hyper spectral and multispectral images [6]. Spectral unmixing technique is used to estimate end members and abundances of the hyper spectral image [7]. Using CNMF, the hyper spectral and multispectral images are iteratively unmixed to improve the quality of the end member and abundance map. But, CNMF offers low performance in terms of spectral preservation. Hence, estimation of spectral difference component is necessary to spectrally adjust the image. This leads to additional computations and thus the computational complexity is increased. Also, when the wavelength between the two images are different, resolution enhancement is reduced. This leads to the generation of low spatial resolution image. Hence, in order to overcome these disadvantages and to improve the spatial resolution and to preserve the spectral information in hyper spectral images, a block based fusion method is proposed.

**Proposed Work:** The proposed algorithm deals with the fusion of multispectral and hyper spectral data. The main objective of this algorithm is to improve the spatial resolution and to preserve the spectral information in hyper spectral images, by fusing it with multispectral images having higher spatial resolution and partially different or non-overlapping wavelength ranges. The algorithm consists of the following two phases.

- Simulation Phase
- Fusion Phase

In the simulation phase, a Simulated Multi Spectral Band (SMSB) is generated using the hierarchical clustering technique and block principal pivoting algorithm. The fusion phase includes a block - based fusion technique based on the association of hyper spectral and multispectral bands.

**Simulation Phase:** Initially, a high spectral and low spatial resolution hyper spectral image was generated by applying a  $5 \times 5$  averaging filter for each band of the

reference image. Second, a high spatial and low spectral resolution multi spectral image has been generated by filtering the reference image with a Gaussian low pass filter.

Now, the hyper spectral image with a low spatial resolution and multispectral image with a high spatial resolution are defined as  $HS \in \mathbb{R}^{h_{col} \times h_{row} \times h}$  and  $MS \in \mathbb{R}^{m_{col} \times m_{row} \times m}$  where  $h_{col}$  and  $h_{row}$  are the total number of pixels in a column and row, respectively, in a single band of a hyper spectral image.  $m_{col}$  and  $m_{row}$  are the total number of pixels in a column and a row, respectively, of a multispectral image.  $h$  and  $m$  denote the total number of bands in a hyper spectral and multi spectral image, respectively. The end members of hyper spectral and multispectral images are generated using the hierarchical clustering algorithm.

**Hierarchical Clustering Algorithm:** Hierarchical clustering algorithm is used for the end member extraction process. The goal of this algorithm is to recover the constitutive materials (the end members) present in the hyper spectral and multispectral images. This algorithm clusters the pixels in an image in a hierarchical manner.

The pixels of an image  $M^{m \times n}$  are clustered into  $r$  disjoint clusters each corresponding to a different end member. It is assumed that each pixel contains exactly one material and no noise is present. This algorithm uses rank two non-negative matrix factorization. The motivation for this choice is two-fold,

- NMF corresponds to the linear mixing model for HS images and
- Rank-two NMF can be solved efficiently, avoiding the use of an iterative procedure as in standard NMF algorithms.

Consider a HS image matrix  $M^{m \times n}$  with  $r$  end members. The main aim of the algorithm is to split the image into  $r$  disjoint clusters. Mathematically, a matrix  $M^{m \times n}$  is  $r$ -separable if it can be written as in equation (1)

$$M = WH = W [I_r, H'] \Pi \quad (1)$$

where  $W \in \mathbb{R}^{m \times r}$ ,  $H' \geq 0$  and  $\Pi$  is a permutation matrix.

Each column of  $W$  is the spectral signature of an end member. Initially, a non-negative matrix  $M$  with rank two is split into two matrices  $W$  and  $H$ . All columns of  $M$  can be represented exactly as nonnegative linear combinations of two nonnegative vectors and therefore the exact NMF is always possible for  $r = 2$ .

Singular Value Decomposition is used to reduce a large matrix into significantly small matrix. Here, it is used to split  $M$  into  $[U \ S \ V^T]$  where  $U$ ,  $S$ ,  $V^T$  are the singular vectors of  $M$ .  $U$  is an  $m \times k$  orthogonal matrix,  $S$  is a  $k \times k$  diagonal matrix ranked from greatest to least,  $V$  is  $n \times k$  orthogonal matrix and  $U^T U = V^T V = I$ .

Each singular value in  $S$  corresponds to a two-dimensional image built from a column in  $U$  and a row in  $V$ . Now,  $X$  is the input matrix, which is found using the equation (2)

$$X = S \cdot V \quad (2)$$

Then, Successive Projection Algorithm is used for extracting two cluster indices. The column of the input matrix  $X$  with maximum norm is selected using the equation (3)

$$k = \arg \max_j \|X_{\cdot j}\|_2 \quad (3)$$

The input matrix  $X$  is updated using the update rule given in equation (4)

$$X \leftarrow (I - X_{\cdot k} \cdot X_{\cdot k}^T / \|X_{\cdot k}\|_2^2) X \quad (4)$$

A cluster  $K$  is formed from the updated values of  $k$ . Now  $W$  and  $H$  is obtained using the equations (5) and (6)

$$W = \max (0, USV(:, K)) \quad (5)$$

$$H = \arg \min_{X=0} \|M - WX\|_F^2 \quad (6)$$

Now,  $x[i]$  is calculated using the formula given in equation (7)

$$x[i] = H(1, i) / (H(1, i) + H(2, i)) \text{ where } i = 1 \dots K \quad (7)$$

Then the threshold value  $\delta$  is chosen in such a way that it satisfies the two conditions

- The clusters are balanced, that is the two clusters contain same no of elements.
- The clusters are stable that is, if the value of  $\delta$  is slightly modified, then only a few points are transferred from one cluster to the other.

Here,  $\delta$  is chosen as 0.5. Now, two clusters  $C1$  and  $C2$  are formed such that

$C1 = i$  when the value is greater than or equal to 0.5.

$C2 = i$  when the value is less than 0.5

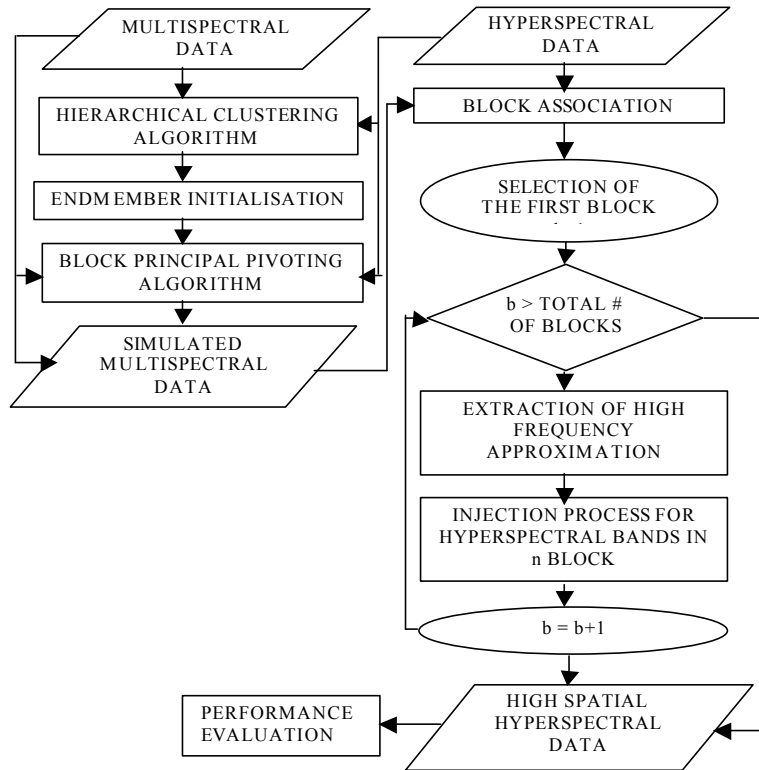


Fig. 1: Workflow of Proposed System

From the clusters c1 and c2, select any one and the above process is repeated until we get all the endmembers.

H2NMF can handle better background pixels and noise. It outperforms standard end member extraction algorithms such as VCA and SPA [8].

**Block Principal Pivoting Algorithm:** After extracting the end members (W) using the hierarchical clustering algorithm, the abundance or fraction maps (H) for individual end members, which are sets of corresponding fractions that indicate the proportion of each end member present in a pixel are found out using the block principal pivoting algorithm. Given an image matrix  $M^{m \times n}$  and its end members matrix  $W^{m \times r}$ , this algorithm finds abundance matrix  $H^{r \times n}$  such that the given optimization condition is satisfied.

$$\text{minimize } \|WH - M\|_F^2 \quad (8)$$

where  $M = 0$  element wise.

The optimality condition for the above equation is given as

$$Y = W^T * W * H - W^T * M \quad (9)$$

**Fusion Phase:**

$$Y = 0 \quad (10)$$

$$Y_i * H_i = 0, i = 1 \dots n \quad (11)$$

The algorithm is summarized as follows.

- Compute  $W^T * W$  and  $W^T * M$ .
- The index set  $\{1 \dots n\}$  is split into two subsets F and G such that  $F \cup G = \{1 \dots n\}$  and  $F \cap G = \emptyset$ .
- Let  $W_F$ ,  $W_G$ ,  $H_F$  and  $H_G$  denote the subsets of variables with corresponding indices and let  $M_F$  and  $M_G$  denote the sub matrices of M with corresponding column indices.
- Initialize,  $W_G = 0$  and  $H_F = 0$ .
- By this construction,  $W = (W_F, W_G)$  and  $H = (H_F, H_G)$  and any values of  $W_F$  and  $H_G$  always satisfies the equation  $W_F * H_G = 0$ .
- Now, compute  $W_F$  and  $H_G$  using the equations (12) and (13)

$$W_F = \text{argmin}_{W_F} \|W_F H_F - M\|_2^2 \quad (12)$$

$$H_G = W_G^T (W_F H_F - M) \quad (13)$$

- Compute  $W_F$  first and substitute it in the next equation to obtain  $H_G$ . The pair  $(W_F, H_G)$  is called the complementary basic solution.
- If the complementary basic solution satisfies the condition  $W_F = 0$  and  $H_G = 0$ , then the solution is feasible.
- Else, the solution is infeasible. Now, update F and G by exchanging columns and repeat the other steps until a feasible solution is reached.

Thus, the block principal pivoting algorithm is generally the most efficient method for computing the abundance matrix.

**Generating Approximate Component:** The approximate component (AC) which has a high spatial resolution and approximated spectral information in the missing wavelength range of MS is computed using the equation (14)

$$AC = W_{HS} * H_{MS} \quad (14)$$

where  $W_{HS}$  is the end member matrix of the hyper spectral image and  $H_{MS}$  is the abundance matrix of the multispectral image.

**Generating Simulated Multispectral Data:** The simulated multispectral image (SMS) is defined as an integrated band set that includes AC and the original MS bands, such that the SMS covers the entire wavelength range of HS and it has a higher spatial resolution.

**Fusion Phase:** In fusion phase, a block is formed by the association of a hyper spectral band and a simulated multispectral band to preserve both the spectral information of HS and the spatial information of MS.

**Extraction of High Frequency Approximation:** After estimating the blocks, the high frequency (HF) information is calculated from the simulated Multispectral image. The  $HF^m$  is given by equation (15)

$$HF^m = SMS^m - SMS^{*m} \quad (15)$$

where m is the number of simulated multispectral image that correspond to a block b and  $SMS^{*m}$  is the gaussian low-pass-filtered simulated multispectral band.

**Generating Fused Hyperspectral Bands (FHS):** Finally, the fused hyperspectral band (FHS) in block b is produced using the equation (16)

$$FHS^n = HS^n + (HF^m * P^n) \quad (16)$$

where  $HS^n$  is the input hyper spectral image,  $HF^m$  is the extracted high frequency approximation and  $P^n$  is the representative pan sharpening coefficient. It is determined based on the covariance of  $HS^n$  and  $SMS^m$  over the variance in  $SMS^m$ .

**Performance Analysis:** To evaluate the qualities of the fused result from the proposed algorithm, the statistical measurements [9] used are

- Root mean Square Error (RMSE),
- Correlation Coefficient (CC),
- Spectral Angle Mapper (SAM),
- Universal Image Quality Index (UIQI),

**Root Mean Square Error:** For the spectral and spatial quality analyses of fused images, the Root Mean Square Error (RMSE) is often used. The RMSE represents the sample standard deviation of the differences between reference and fused image values. RMSE is a good measure of accuracy and is calculated using the following formula

$$RMSE = \text{Square Root } (\sum(\text{ERROR}^2)/n) \quad (17)$$

$$\text{ERROR} = \text{REF} - \text{FHS} \quad (18)$$

where  $n$  is the number of pixels,  $\text{REF}$  represents the reference image and  $\text{FHS}$  represents the fused hyperspectral image. For good fusion results, the value of RMSE must be minimum.

**Correlation Coefficient:** The Correlation Coefficient (CC) presents the correlation between the original and fused images and evaluates the similarity of the fused image to the reference image. The ideal value of correlation coefficient is 1. CC is calculated using the following formula

$$CC = \frac{\sum_i \sum_j (\text{REF}(i, j) - \overline{\text{REF}})(\text{FHS}(i, j) - \overline{\text{FHS}})}{\sqrt{\sum_i \sum_j (\text{REF}(i, j) - \overline{\text{REF}})^2 \sum_i \sum_j (\text{FHS}(i, j) - \overline{\text{FHS}})^2}} \quad (19)$$

where CC is the Correlation Coefficient,  $\text{REF}$  is the reference image,  $\text{FHS}$  is the fused image and  $i$  and  $j$  refer to the pixel location in the image. and is the mean value of the reference and fused image respectively.

**Spectral Angle Mapper:** The Spectral Angle Mapper (SAM) is a suitable index for characterizing multispectral and hyper spectral images. SAM represents the absolute value of the spectral angle between the two spectra, which are transformed into vectors. It is calculated using the following formula

$$SAM = \arccos(\langle \text{VREF}, \text{VFHS} \rangle / \|\text{VREF}\| \|\text{VFHS}\|) \quad (20)$$

where  $\text{VREF}$  denotes the generic pixel vector element of a reference image and  $\text{VFHS}$  denotes the generic pixel vector element of the fused image. The SAM is closer to zero when the fusion results are more spectrally similar to the reference image.

**Universal Image Quality Index:** Universal Image Quality Index (UIQI) is an index that models any distortion between two images by considering the loss of correlation, luminance distortion and contrast distortion [10]. UIQI is calculated using the following formula

$$UIQI = \frac{4 * \sigma(\text{REF}, \text{FHS}) * \overline{\text{REF}} * \overline{\text{FHS}}}{(\sigma^2 \text{REF} + \sigma^2 \text{FHS})(\overline{\text{REF}}^2 + \overline{\text{FHS}}^2)} \quad (21)$$

where  $\sigma(\text{REF}, \text{FHS})$  is the covariance between the reference and fused image,  $\sigma \text{REF}$  is the standard deviation of the reference image,  $\sigma \text{FHS}$  is the standard deviation of the fused image and is the mean value of the reference and fused image respectively. The dynamic range of UIQI is  $[-1, 1]$ . The best value of 1 is achieved when the reference image is equal to the fused image. The worst value of -1 indicates bad fusion result.

## RESULTS AND DISCUSSION

The proposed fusion method is tested using three sets of hyperspectral and multispectral image pairs and its performance is evaluated using the performance measures given above.

If there is no quality difference between two images (reference and fused), then root mean square error is zero, correlation coefficient is one, spectral angle mapper value is zero and the universal image quality index value is one.

**Data Set:** The proposed algorithm is tested using the hyper spectral data set collected by the hyperspectral sensor HYDICE (HYperspectral Digital Imagery Collection Experiment).

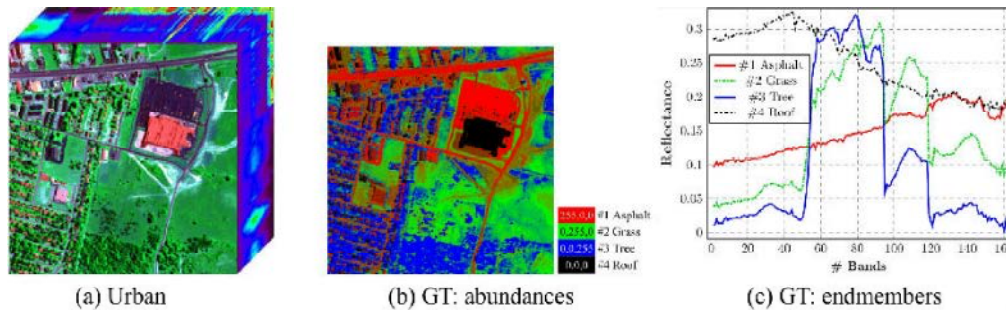


Fig. 2: Urban Data Set and its Ground Truth

It is a 210 band image. There are 307 x 307 pixels in each band each of which corresponds to a 2 x 2 m<sup>2</sup> area. The wavelength ranges are from 400 nm to 2500 nm, resulting in a spectral resolution of 10 nm. After the channels 1-4, 76, 87, 101-111, 136-153 and 198-210 are removed due to dense water vapor and atmospheric effects. Thus, the resulting data set contains 162 bands. Three versions of ground truth, containing 4, 5 and 6 end members respectively, are present in the data set. Figure 2 shows the urban data set with its 4 end member version.

## RESULTS

The hyper spectral and multispectral data sets for the same scene is not available presently. Hence, they are generated using the software ENVI. Figure 3 and Figure 4 are the RGB composite of hyper spectral and multispectral data sets. The bands 53, 35 and 10 are used for generating the image.

Table 1 describes the three sets used for analysis.

The proposed block based fusion method is compared with the existing CNMF based fusion method and the results are tabulated in Table II. The set of hyper spectral and multispectral images of data set S1 are given in Figure 5 and 6.

Figure 7 and 8 shows the generated simulated multispectral band and fused high spatial resolution hyper spectral image of data set S1 respectively.

The tabulated readings are plotted in a graph for better visualisation of results. Figures 8, 9, 10 and 11 shows the comparison of various performance measures.

From the tabulated and plotted performance measures it is inferred that the proposed block based fusion algorithm using hierarchical clustering has a better performance compared to the existing CNMF based fusion method.



Fig. 3: Hyperspectral Image



Fig. 4: Multispectral Image



Fig. 5: Hyperspectral image of data set S1

Table 1: Data sets used for analysis

Data Set	Hyper spectral Image		Multispectral Image	
	Bands	Wavelength	Bands	Wavelength
S1	20 to 24	468 to 486 nm	70 to 74	873 to 927 nm
S2	35 to 39	543 to 567 nm	85 to 89	1088 to 1147 nm
S3	50 to 54	650 to 687 nm	110 to 114	1451 to 1506 nm

Table 2: Fusion Results

Data Set	RMSE		CC		SAM		UIQI	
	CNMF Based Fusion	Block Based Fusion	CNMF Based Fusion	Block Based Fusion	CNMF Based Fusion	Block Based Fusion	CNMF Based Fusion	Block Based Fusion
S1	57.28	8.71	0.36	0.998	0.66	0.041	0.036	0.991
S2	57.29	9.39	0.39	0.997	0.61	0.041	0.033	0.991
S3	62.22	10.19	0.37	0.998	0.63	0.046	0.038	0.989



Fig. 6: Multispectral image of data set S1



Fig. 7: Simulated Multispectral Band of Data Set S1



Fig. 7: Fused Image of Data Set S1

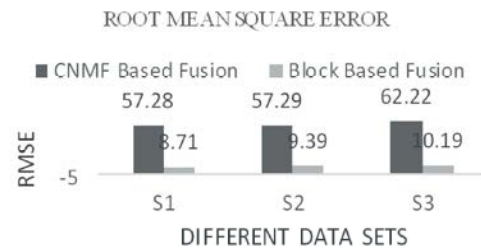


Fig. 8: Comparison of RMSE



Fig. 9: Comparison of CC

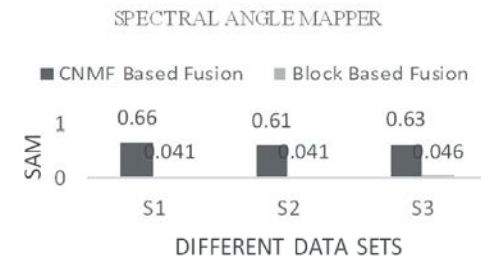


Fig. 10: Comparison of SAM

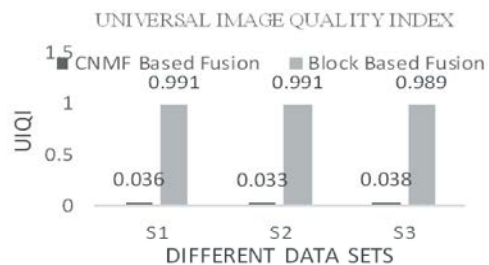


Fig. 11: Comparison of UIQI

## CONCLUSION

A block based image fusion algorithm is proposed to enhance the spatial quality and to preserve the spectral information in hyper spectral images using multispectral images having high spatial resolution and partially different wavelength ranges compared to hyper spectral images. The proposed algorithm performs a band simulation and group's bands of hyper spectral and multispectral images into blocks by comparing the correlation between the simulated multispectral band and the hyperspectral band. Then, the high frequency information is extracted from the simulated multispectral band and is fused with the hyper spectral image. The fusion results from the proposed algorithm demonstrated a more effective spatial enhancement and better spectral preservation when compared with the existing fusion method.

## REFERENCES

1. Gary A. Shaw and Hsiao - hua K. Burke, 2003. Spectral Imaging for Remote Sensing' Lincoln Laboratory Journal, 14(1): 3-28.
2. Nirmal Keshava, 2003. A Survey of Spectral Unmixing Algorithms, Lincoln Laboratory Journal, 14(1): 55-78.
3. Bruno Aiazzi, Stefano Baronti, Member, IEEE, Franco Lotti and Massimo Selva, 2009. A Comparison between Global and Context - Adaptive Pan sharpening of Multispectral Images, IEEE Geoscience and Remote Sensing Letters, 6(2): 302-306.
4. Jaewan Choi, Junho Yeom, Anjin Chang, Younggi Byun and Yongil Kim, Member, IEEE, 2013. Hybrid Pan sharpening Algorithm for High Spatial Resolution Satellite Imagery to Improve Spatial Quality, IEEE Geoscience and Remote Sensing Letters, 10(3): 490-494.
5. Dong Jiang, Dafang Zhuang and Yaohuan Huang, 2013. Investigation of Image Fusion for Remote Sensing Application, New Advances in Image Fusion, <http://dx.doi.org/10.5772/56946>, pp: 1-18.
6. Naoto Yokoya, Student Member, IEEE, Takehisa Yairi and Akira Iwasaki, 2012. Coupled Nonnegative Matrix Factorization Unmixing For Hyperspectral and Multispectral Data Fusion, IEEE Transactions on Geoscience and Remote Sensing, 50(2): 528-537.
7. Xuesong Liu, Wei Xia, Bin Wang, Member, IEEE and Liming Zhang, Senior Member, IEEE, 2011. An Approach Based on Constrained Nonnegative Matrix Factorization to Unmix Hyperspectral Data, IEEE Transactions on Geoscience And Remote Sensing, 49(2): 757-772.
8. José, M.P. Nascimento, Student Member, IEEE and José M. Bioucas Dias, Member, IEEE 2005. Vertex Component Analysis: A Fast Algorithm to Unmix Hyperspectral Data, IEEE Transactions on Geoscience and Remote Sensing, 43(4): 898-910.
9. Lucien Wald. 2000. Quality of high resolution synthesized images: Is there a simple Criterion?' Proceedings of the third conference "Fusion of Earth data:", Sophia Antipolis, France, pp: 99-105.
10. Zhou Wang, Student Member, IEEE and Alan C. Bovik, Fellow, IEEE, 2002. A Universal Image Quality Index' IEEE Signal Processing Letters, 9(3): 81-84.