Spatial Resolution Enhancement Of Hyperspectral Image By Negative Abundance Oriented Spectral Unmixing

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***Abstract*— Hyperspectral images possess high spectral resolution, and are capable to give spectral information of different elements in the scene. The spatial resolution of hyperspectral image is very low. This leads to mixing of pixels. Spectral Unmixing algorithms are the most extensively used hyperspectral image analysis techniques for decomposing the mixed pixels. However spectral unmixing does not enhance the spatial resolution. In order to enhance the spatial resolution of hyperspectral image we propose a Hyperspectral-Multispectral image fusion method. The image fusion is based on a negative abundance oriented hyperspectral unmixing algorithm. The algorithm is tested with images from Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) data.**

***Index Terms*— Hyperspectral Imaging, Multispectral Images, Linear Mixing Model, Spectral Unmixing, Endmember extraction algorithm, Resolution Enhancement.**

I. Introduction

Hyperspectral imaging is a class of Spectroscopy. Hyperspectral sensors collects information over hundreds of narrow spectral bands covering the visible to short infrared wavelength range and thus the image contain hundreds of spectral channels per pixel. This high spectral resolution allows for deriving spectral signatures of each pixel. The main drawback of hyperspectral image (HSI) is that, its spatial resolution is very low.

The low spatial resolution leads to mixing of pixel. Spectral unmixing is an important task in hyperspectral image analysis. Spectral unmixing decomposes mixed pixels into a collection of endmember signatures and their abundance fractions. Even though spectral unmixing provides spectral information of the scene, it does not give any spatial information; therefore there is a need for spatial resolution enhancement. One way is to fuse the hyperspectral image with a high spatial resolution multispectral image (MSI).

Many image fusion techniques have been developed for the fusion. Among them the first fusion method was a wavelet based fusion [1], its performance depends on the spatial and spectral resampling. A MAP (maximum a posteriori) estimation based fusion is explained in [2]. In [3] a Coupled Nonnegative Matrix Factorisation (CNMF) Unmixing based fusion is proposed according to the spectral unmixing model, which alternately unmixes MSI and HSI by NMF. It is based on the linear mixing model (LMM) which expresses each pixel in the HSI in a linear model.

CNMF method produces high spatial resolution hyperspectral image, by the endmember spectra of low spatial resolution HSI and the abundance fractions of high spatial resolution MSI. CNMF has shown better results than MAP.Another unmixing based fusion is proposed in [4], which is applied on sub images rather than the whole image.

A. Problem Formulation

The mixed pixels in HSI are a mixture of more than one distinct endmembers. Thus each hyperspectral pixel can be represent as a linear combination of several endmember spectra and their fractional abundance. The LMM of HSI (X) is,

$$X = EA + N_X. \tag{1}$$

where E is the endmember matrix and A is the abundance matrix, N_X is nothing but the noise. The low spatial resolution HSI can be denoted as a $l \times m$ matrix representation, where l is the number of bands and m is the number of pixels. The high spatial resolution MSI can be denoted as a $p \times n$ matrix representation, where p is the number of bands and n is the number of pixels, which implies $l<p$ and $n>m$. Both the HSI and MSI can be represent in LMM. The abundance matrix of MSI image contains spatial information about the scene, where as the endmember matrix of HSI contains spectral information about the scene. The LMM representation of HSI (X) and MSI (Y) is [4],

$$X \approx EA_h. \tag{2}$$

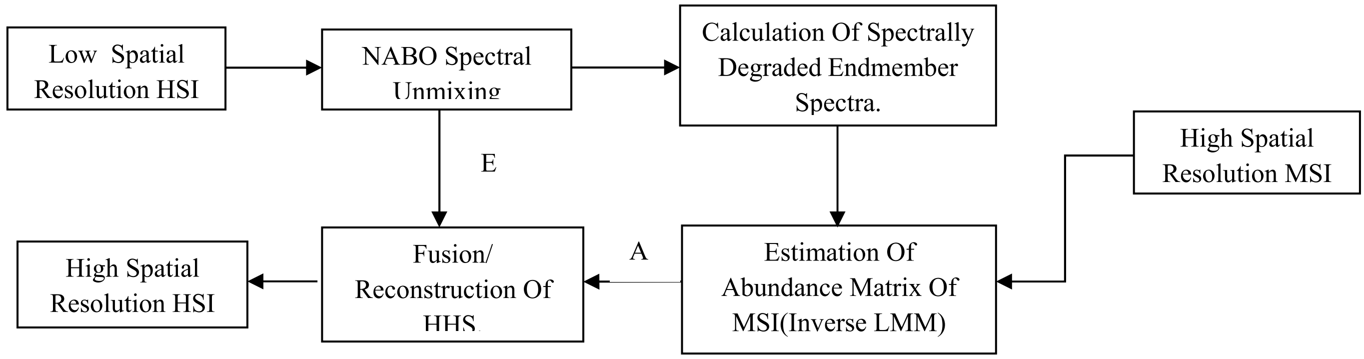


Fig. 1. Overview Of Unmixing Based Fusion.

$$Y \approx E_m A. \quad (3)$$

where A_h is the spatially degraded abundance matrix and $E_m$is the spectrally degraded endmember matrix. In order to obtain a high spatial and high spectral resolution hyperspectral image (HHS), endmember should be derived from HSI and abundance should be from MSI. The spectral unmixing based fusion requires accurate extraction of endmember by a proper Endmember Extraction(EE) algorithm [5]-[8]. The CNMF fusion is based on NMF (Nonnegative Matrix Factorization) [5] EE algorithm, where as in [4] the vertex component analysis (VCA) [6] is adopted. All these EE algorithms are lengthy and complex processes. The proposed fusion uses Negative Abundance Oriented (NABO)[9] spectral unmixing algorithm which provides a full SU chain and relatively simple. The fusion method proposed in this paper is an extension of NABO algorithm [9] in HSI fusion.

The rest of the paper is organized as follows. The NABO unmixing procedure is explained in Section II. The Section II describes the proposed fusion frame work in detail. Section III gives the results and discussions. Finally, conclusions are given in Section IV.

II. Proposed Fusion Method

The proposed fusion based spatial resolution enhancement technique reconstructs the HHS image via NABO spectral unmixing technique. The full fusion process is shown in Fig.1.The fusion combines spectral properties of HSI and spatial properties of MSI. The algorithm will first unmix the HSI. The NABO unmixing in [9] is adopted here, which gives better result than a VCA [6] EE algorithm. The unmixing gives endmember matrix from HSI. The spatial information is then extracted from MSI by inverse LMM.

The proposed method also includes a denoising step prior to the unmixing process. The photon limitation occurred in spectral imaging cause noise in the extracted images. A denoising procedure based on Non - Local PCA [10] has been adopted here to remove noise in the extracted image. It is a patch-based denoising technique, in which PCA (Principal Component Analysis) is used for denoising images contaminated by Poisson noise. Thus the proposed algorithm can also be performed in a noisy environment.

A. Negative Abundance Oriented Spectral Unmixing

NABO unmixing is based on the negative abundance of endmembers. A minimization process guided by an energy objective function is used to extract the optimal set of endmembers. The energy function J can be expressed by negative abundance as[9],

$$\arg\min_{E} J(E). \quad (4)$$

The complete NABO process is given in Algorithm 1. NABO unmixing gives the spectral information of HSI image. The advantage of NABO unmixing over VCA in [6] is that it provides full SU chain (EE and Abundance Estimation) in a single algorithm; also it is faster than VCA. The simplicity in NABO algorithm reduces the complexity of whole fusion process.

Algorithm1: Procedure for NABO unmixing

Preprocessing Step: Poisson noise reduction with Non-Local PCA .

INPUT: HSI.

OUTPUT: Endmember set, Spatially degraded Abundance matrix.

1) Selection of initial endmember set.(p).

2) Calculation of abundances(a) for each pixel x(Inverse LMM).

$$\mathrm{a} = \mathrm{E}^{\dagger}\mathrm{x} \text{ where, } \mathrm{E}^{\dagger} = (\mathrm{E}^{\mathrm{T}}\mathrm{E})^{-1}\mathrm{E}^{\mathrm{T}}.$$

3) Sort the abundance values (Most minimum first).

4) Calculation of the energy objective function (J). For the jth pixel J will be;

$$J = \left|\sum_{j} \beta_j\right|,$$

$$where\ \beta_j = \begin{cases} \min_i(s_{ij}) & if\ \min_i(s_{ij}) < 0 \\ 0 & if\ \min_i(s_{ij}) \geq 0 \end{cases}$$

i keeps tracks of every endmember.

5) Set an iteration counter, which decrement by one at each step. Update the endmember set by replacing each element with pixel having minimum abundance.

6) Calculate the energy function with new endmember set. If energy function shows a decrement then fix the replacement.

7) Continue the process till the counter exhaust.

B. Hyperspectral-Multispectral Image Fusion

In the proposed fusion method unmixing step gives the spectral information for the output HHS. The spatially degraded endmember matix for the MSI is obtained by the spectral downsampling of endmember matrix of HSI. The spatial information is obtained from MSI through inverse LMM. This fusion procedure is summarised in Algorithm 2.

Algorithm 2: Procedure for HSI-MSI Fusion.

INPUT1: HSI(X)
INPUT2: MSI(Y)
OUTPUT: High spatial and spectral resolution Hyperspectral Image (HHS), Z.

1) Endmember extraction of low spatial resolution HSI with initial endmember set p.

$$E = NABO(X, p)$$

2) Calculation of spectrally degraded endmember for MSI(E_m) by spectral downsampling.

3) Inverse LMM of MSI.

$$A = E_m^{-1} Y$$

4) Calculation of spatially degraded abundance matrix for HSI i.e. A_h.

5) Recalculation of E.

$$E = (XA_h^T)(A_h A_h^T)^{-1}$$

6) Fusion step: Generation of HHS image Z.

$$Z = EA$$

III. EXPERIMENTAL RESULTS

The experiments have been done on two inputs. The first scene is taken over Cuprite mining district in Nevada, captured by Airborne Visible/Infrared Imaging Spectrometer (AVIRIS), containing 250×191 pixel with 224 spectral bands ((400-2500nm). The second scene is taken over the Indian Pine by the AVIRIS sensor, containing 120×120 pixels with 224 spectral bands in the 400-2500-nm region; we use only 204 spectral bands after removing the bands covering the water absorption region: 104-108, 150-163, and 220.

The low spatial resolution HSI image is generated by the Gaussian downsampling of the HHS(i.e.Reference image) image and the low spectral resolution MSI is by the uniform spectral downsampling of the HHS image corresponding to Landsat TM bands 1-5 and 7 covering the following spectral regions: 450-520, 520-600, 630-690, 760-900, 1550-1750, and 2080-2350 nm [11].

A. Performance Metrics

Three different measurements are utilized to evaluate the performance of proposed fusion method: the peak Signal to Noise Ratio (PSNR) to evaluate the spatial quality, the Spectral Angle Mapper (SAM) to evaluate the spectral quality and the Structural Similarity Index (SSIM) which is based on the human vision system. The PSNR is expressed by the mean square error (MSE) as,

$$PSNR_k = 10log_{10}\left(\frac{MAX_k^2}{MSE_k}\right) dB. \tag{5}$$

where MSE can be expressed as,

$$MSE_k = \frac{1}{n}\sum_{i=1}^{n}(Z - EA)_{i,k}^2 \tag{6}$$

where MAX_k is the maximum pixel value in the kth band. The SAM [5] between two spectra z and z' is defined as follows:

$$SAM = \arccos\left(\frac{\langle z, z' \rangle}{\|z\|_2 \|z'\|_2}\right) \tag{7}$$

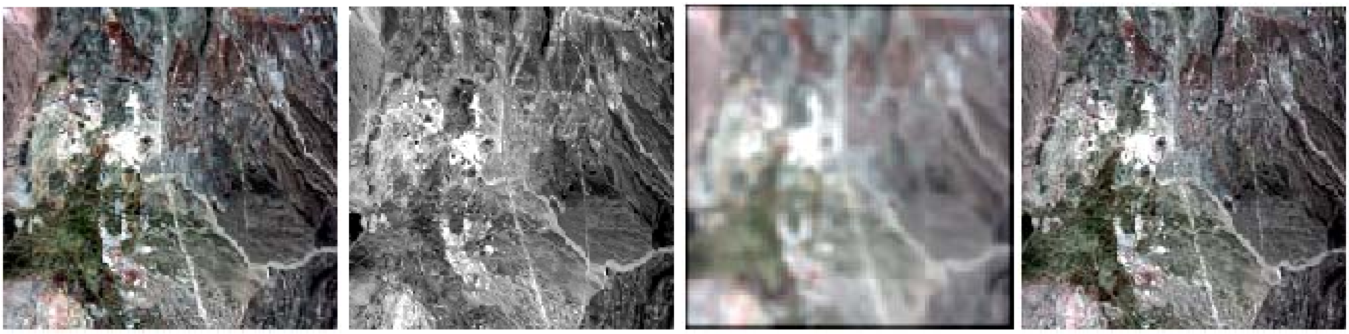
The SSIM is defined as follows;

$$SSIM = \left(\frac{(2\mu_Z\mu_{EA}+C_1)(2\sigma_{ZEA}+C_2)}{(\mu_Z^2+\mu_{EA}^2+C_1)(\sigma_Z^2+\sigma_{EA}^2+C_2)}\right). \tag{8}$$

where Z and EA represent the reference and estimated HHS images and μ and σ are the mean and variance or covariance respectively. The constants C_1 and C_2 are added to avoid an unstable result when $\mu_Z^2 + \mu_{EA}^2$ or $\sigma_Z^2 + \sigma_{EA}^2$ is close to zero.

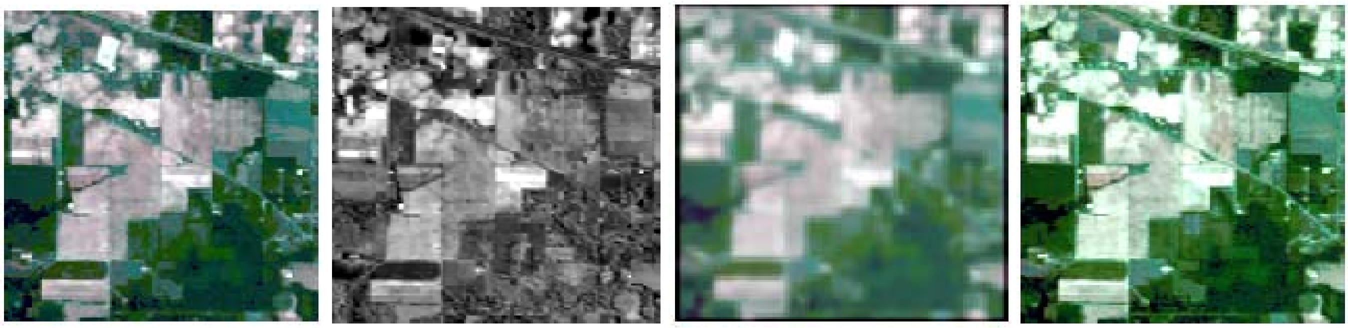
B. Fusion Results

The Fig.2 and Fig.3 shows the fusion results for both the inputs. The accuracy of proposed fusion algorithm can be evaluated by comparing the spectral signatures of input low spatial resolution HSI and fused image. Fig.4 and Fig.5 shows the spectral signatures of reference and output image for both the inputs. Comparing the spectral profile of the two images



(A) (B) (C) (D)

Fig . 2. (A) The Reference Image, (B) The high spatial resolution Multispectral Image (C) Low spatial resolution Hyperspectral Image (D) The Fusion Output (For the Input CUPRITE).



(A) (B) (C) (D)

Fig. 3. (A) The Reference Image, (B) The high spatial resolution Multispectral Image (C) Low spatial resolution Hyperspectral Image (D) The Fusion Output (For the Input INDIAN PINE)

similarities can be found in the curves. Hence the spectral properties of the image is maintained.

The performance of proposed fusion can be quantitatively evaluated using performance metrics in (5), (7) & (8) the simulated results are summarized in Table I. In Table II the results are compared against VCA based fusion in [4].

IV. Conclusion

The proposed fusion based spatial resolution enhancement technique reconstructs the HHS image by NABO spectral unmixing. It combines spectral qualities of Hyperspectral image and spatial qualities of multispectral images. The existing fusion method uses complex unmixing algorithms like VCA and they need spatial and spectral relationships between inputs. The advantage of proposed method is that it applies NABO unmixing for the fusion and gives similar results even without the knowledge of spatial and spectral relationships between inputs. The proposed method can deal with noisy hyperspectral images, because it performs a denoising algorithm as preprocessing step.

TABLE I. Performance Metrics

Parameters	Cuprite	Indianpine
PSNR(dB)	70.5955 dB	45.4864
SSIM	0.9790	0.9438
SAM	1.5629	1.5666

TABLE II. Comparison With VCA Based Fusion

Fusion Methods	PSNR(dB)	
	Cuprite	Indianpine
NABO based fusion.	70.5955	45.4864
VCA based fusion.	34.9050	37.9387

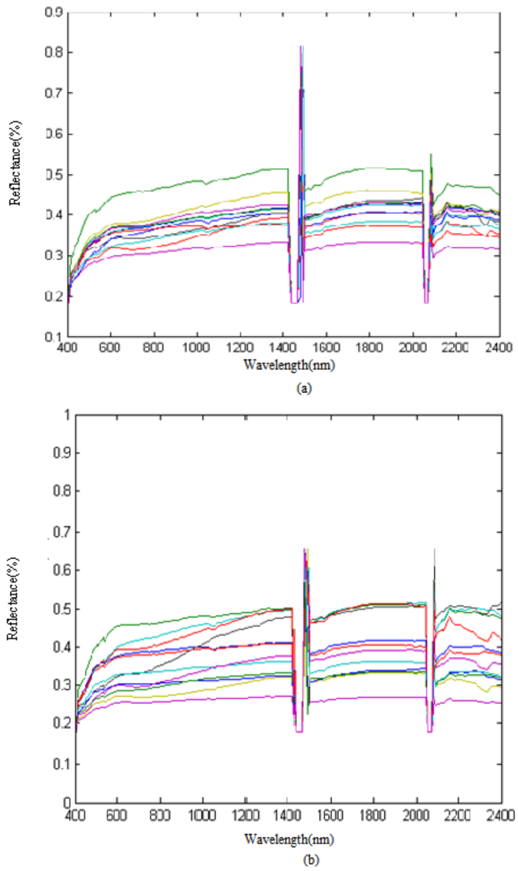


Fig. 4. Spectral Profile for (a) HSI, (b) Fusion Output.(For Cuprite).

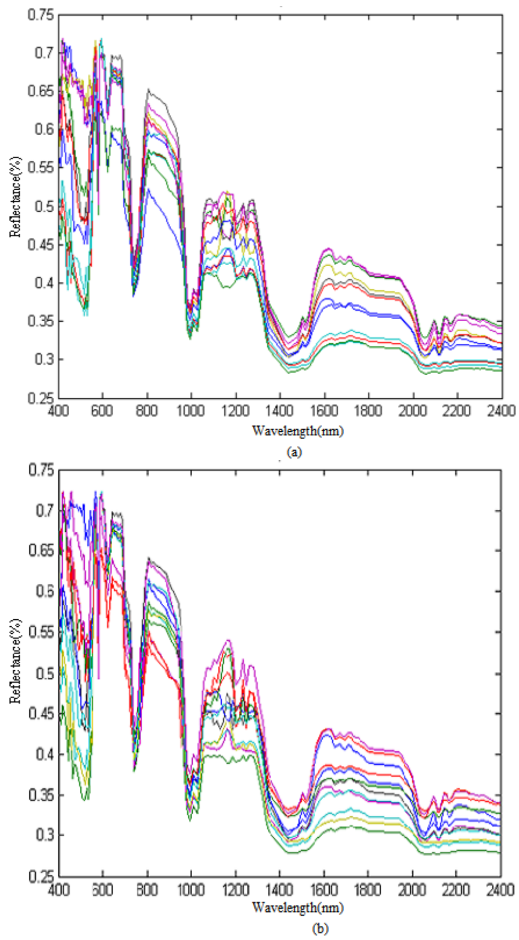


Fig. 5. Spectral Profile for (a) HSI, (b) Fusion Output.(For Indian Pine).

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