International Journal of Engineering and Advanced Technology (IJEAT)
ISSN: 2249-8958 (Online), Volume-5 Issue-5, June 2016

Super Resolution of Hyper Spectral Image Based on NABO Spectral Unmixing

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Abstract—Hyperspectral imaging has become an important image analysis technique in remote sensing. Processing and enhancing hyperspectral images are a difficult task. The spectral information contained in the hyperspectral images are extracted by spectral unmixing techniques. This paper proposes a novel method for enhancing spatial resolution of hyperspectral images based on spectral unmixing. Many applications needs images containing both high spectral resolution and high spatial resolution. In this paper a NABO (Negative Abundance Oriented) spectral unmixing based hyperspectral-multispectral image fusion algorithm is proposed for the purpose of enhancing the spatial resolution of hyperspectral image(HSI). As a result, a high-spatial-resolution HSI is reconstructed based on the high spectral characters of the HSI represented by endmember spectra and the high spatial characters of the multispectral image(MSI) represented by abundance fractions. Experiments were done on Airborne Visible/Infrared Imaging Spectrometer data. NABO unmixing based fusion gives better results than existing Endmember Extraction (EE).

Index Terms— Hyperspectral Imaging, Linear Mixing Model, Spectral Unmixing, Multispectral Images, Endmember Extraction Algorithms, Resolution Enhancement.

I. INTRODUCTION

Over the last decade, Hyperspectral Imaging have become more popular in the field of remote sensing. It has been motivated by the need to extract material information in a scene for many applications. Hyperspectral Images (HSIs) have plethora of applications in areas such as agriculture, hazard monitoring, and classification of land covers etc.

Hyperspectral imaging is a class of spectroscopy in which a complete spectrum or some spectral information is collected at every location on image plane and is processed. HSIs differs from other satellite imaging technique in that it provides a unique spectral signature for each pixel in the image which can be used in identification of various surface materials. The HSI, contain hundreds of narrow spectral channels per pixel. This high spectral resolution makes HSIs perfect for material detection, especially in mining areas by Spectral Unmixing (SU) [1] techniques. land cover requires images having high spectral and spatial resolution, this introduced a need to enhance the spatial resolution of HSIs. Over the last decades many super resolution techniques have been developed for enhancing HSI based on image fusion.

The first fusion method was the wavelet based fusion[2], its performance depends on the spatial and spectral resampling. The authors in [3] have developed a MAP(maximum a posteriori) estimation based fusion method. Another method for HSI super resolution uses spectral unmixing. In this method the endmember spectra containing spectral informations of the scene are extracted from HSI via SU. Next, this spectral information is fused with the abundance map of high spatial resolution MSI. These methods are based on the fact that each hyperspectral pixel can be represented as a Linear Mixing Model(LMM)[1], i.e.,

$$H = AS + N_h \qquad (1)$$

where, A is the endmember spectra and S is their fractional abundance, N_h is nothing but the noise.

A Coupled Nonnegative Matrix Factorisation(CNMF) Unmixing based fusion is proposed according to SU in [4],which alternately unmix MSI and HSI by Nonnegative Matrix Factorization (NMF).In CNMF method high spatial resolution HSI is produced by the endmember signatures of low spatial resolution HSI and the fractional abundance of high spatial resolution multispectral image. CNMF has shown better results than MAP. In [5] another unmixing based fusion is proposed, which generate high spatial resolution HSI with relatively small spectral resolution MSI. This fusion method is applied on sub images rather than the whole image. In this paper a novel spatial resolution enhancement of HIS is proposed, which can deal with situations where knowledgeof observation model is not available. This paper is an extension of the Negative Abundance Oriented (NABO) spectral unmixing algorithm [10] in HSI resolution enhancement. Moreover, this algorithm is applied on subimages and finally the spatial and spectral performance of the procedure is evaluated by comparing it with the fusion method which uses Vertex Component Analysis (VCA) algorithm [5]. The remainder of the paper is organized as follows. The Spectral Unmixing and LMM of HSI are described in Section II. The NABO unmixing procedure is explained in Section III.
In Section IV, the proposed fusion frame work is described in detail. Section V gives the results and discussions. Finally, conclusions are given in Section VI.

II. LINEAR MIXING MODEL

The spatial resolution of the HSI is very low and it results in mixing of pixels, which is the most unique property of spectral images, when compared with RGB colour images. Thus, each pixel in the HSI can be represent in a LMM model given in (1). LMM model describes HSI as a linear combination of several endmembers (purest spectra) and corresponding abundance fractions. Spectral Unmixing decomposes the mixed pixels into a collection of endmembers and abundance fractions.

Manuscript published on 30 June 2016.
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Let l be the number of bands in low spatial resolution HSI with m number of pixels,where as high spatial resolution MSI has p number of bands and n pixels,therefore $l<p$ and $n>m$. HSI as well as the MSI can be defined in LMM using (1).In the fusion context the endmember spectra of MSI will be spectrally degraded where as the abundance information of HSI will be spatially degraded.In the fusion context the endmember spectra of MSI will be spectrally degraded (low spectral resolution) where as the abundance information of HSI will be spatially degraded (low spatial resolution). Thus the LMM in (1) changes as[4],

$$H \approx ES_h \quad (2)$$

$$M \approx A_m S \quad (3)$$

where S_h is the spatially degraded abundance matrix and A_m is the spectrally degraded endmember spectra. The spectral information of an HSI is described by its endmember spectra, while the spatial information is denoted by its fractional abundances. So in order to obtain a high spatial and high spectral resolution hyperspectral image (HHS), endmember should be extracted from HSI and abundance should be from MSI. The methods in[3] and [4] requires the knowledge of spectral and spatial relationship between both sensors. But in practical situation spectral and spatial relationship between HSI and MSI may be unknown,the proposed method deals with such situations. The unmixing based resolution enhancement requires accurate endmember estimation by a proper Endmember Extraction (EE) algorithms [6]-[9]. Many EE algorithms such as VCA ,Minimum Volume Simplex Analysis (MVSA) etc [6]-[9] have been developed for HSIs.

The EE algorithm used in CNMF fusion is NMF [5] algorithm where as in[4] the VCA algorithm is adopted. All these EE algorithms are lengthy and complex processes. NABO is a new EE algorithm which uses only a global optimization function for endmember extraction. NABO is faster and simple than VCA. The proposed fusion uses NABO[10] unmixing algorithm which provides a full SU chain.

III. Negative Abundance Oriented Spectral Unmixing

A negative abundance oriented (NABO) unmixing method can be used to replace the VCA endmember extraction algorithm and unconstrined least square unmixing. NABO is expected to give better results.The NABO method imposes no constraints to the abundance estimation, and the EE is based on the maximum negativity. It covers the three main steps involved in hyperspectral unmixing as a single process. It utilizes the negative abundances as a criterion to identify the endmembers. It uses an iterative process guided by the optimization of a energy objective function J to induce the optimal endmember set [10].

$$arg\ \min_A J(A) \quad (4)$$

The iteration steps for NABO is given in Algorithm 1.Spectral information of the HSI image will be obtained from NABO unmixing. The advantage of NABO unmixing over VCA in[6] is that it gives full SU chain(EE and Abundance Estimation) in a single algorithm, also it is faster than VCA. The NABO algorithm reduces the complexity of whole fusion process.

Algorithm1: NABO spectral unmixing algorithm

INPUT: HSI.

OUTPUT: Endmember set, Spatially degraded Abundance matrix.

1) Randomly select an initial endmember set (p).

2) Calculate Abundance (s) for each pixel h (inverse LMM)

$$s = A^{\dagger} h \ where,\ A^{\dagger} = (A^T A)^{-1} A^T$$

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

4) Optimization of the energy objective function. For the j th pixel,

$$J = \left| \sum_j \beta_j \right|,$$

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

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.

IV. Proposed Fusion Method

The proposed fusion based resolution enhancement method generates the HHS image via NABO spectral unmixing technique. The full fusion chain is shown in Fig. 1.The fusion combines spectral properties of HSI and spatial properties of MSI.The first step is the NABO unmixing of HSI which gives endmember spectra as output.The spatial informations are then extracted from MSI by inverse LMM.

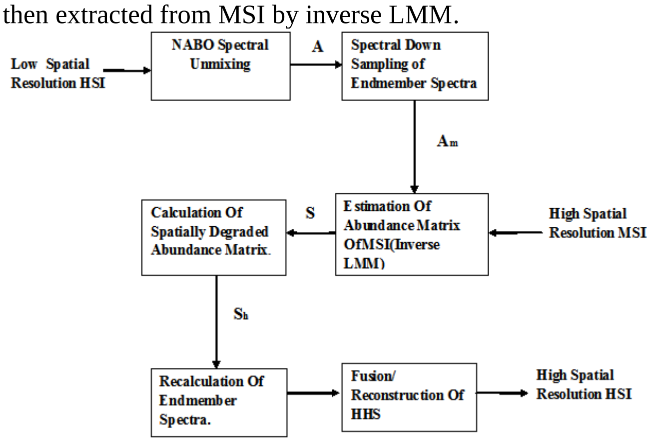

Figure1. Overview of unmixing based fusion

The spatially degraded endmember matix for the MSI is obtained by the spectral down sampling of hyperspectral endmember signatures, then by applying inverse LMM to it abundance matrix can be computed.

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Then using these endmember matrix and fractional abundances output HHS can be generated. This fusion steps are summarized in Algorithm 2.

Algorithm 2: Procedure for HSI-MSI Fusion.

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

1) NABO spectral unmixing of HSI with initial endmember set p.

$$A = NABO(H, p)$$

2) Spectral down sampling of endmember set to generate spectrally degraded endmember for MSI (A_m)

3) Inverse LMM of MSI.

$$S = A_m^{-1} M$$

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

5) Recalculation of A.

$$A = (HS_h^T)(S_h S_h^T)^{-1}$$

6) Fusion step: Generation of HHS image Z.

$$Z = AS$$

In the unmixing step p number of endmembers is extracted from the HSI. Even though this gives accurate results the fact is that p number of endmembers are not actually sufficient for generating HHS image with minimum reconstruction error. In order to reduce the reconstruction error the proposed algorithm is applied to sub images. The Algorithm 2 is applied to each sub images separately and all the outputs are combined to form HHS.

V. EXPERIMENTAL RESULTS

The proposed algorithm is evaluated 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 a Gaussian downsampling of the HHS(i.e.Reference/Input image) image, while the low spectral resolution MSI is a 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[12].

In the first set of experiments Algorithm2 is applied to both the inputs and HHS is generated. The accuracy of results is evaluated using different performance metrics. Three performance metrics utilized are: 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 for the kth band is expressed by the mean square error (MSE) as,

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

where MSE can be expressed as,

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

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:

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

The SSIM is defined as follows:

$$SSIM = \left(\frac{(2\mu_Z\mu_{AS} + C_1)(2\sigma_{ZAS} + C_2)}{(\mu_Z^2 + \mu_{AS}^2 + C_1)(\sigma_Z^2 + \sigma_{AS}^2 + C_2)}\right) \qquad (8)$$

where Z and AS 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 $\mu_Z^2 + \mu_{AS}^2$ or $\sigma_Z^2 + \sigma_{AS}^2$ is close to zero.

In the second set of experiments the subdivision method is used. In the proposed method the adopted set of subdivisions are 240_240; 120_120; 80_80; and60_60. For each single element of a subdivisions Algorithm 2 is applied separately and outputs are generated. Finally all the output elements are concatenated to form the final output.

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 wavelength spectra of input low spatial resolution hyperspectral image and fused image. Fig.4 and Fig.5 shows the wavelength spectra of reference and output image for both the inputs. Comparing the spectral profile of the two images similarities can be found in the curves. Hence the spectral signature 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 summarised in Table I. In Table II the PSNR results are compared against VCA based fusion in [4].

In Table III & Table IV the performance metrics after the subdivision method is summarized. The sub division method increased the PSNR values and all other metrics.

Table I. Performance Metrics.

Parameters	Cuprite	Indianpine
PSNR(dB)	70.5955 dB	45.4864
SSIM	0.9297	0.9438
SAM	1.5666	1.5666

Table II. Comparison with VCA based fusion.

Fusion method	Cuprite	Indian Pine
NABO Based fusion	70.5955	45.4864
VCA Based fusion	34.9050	37.9387

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Table III. Comparison between different subdivisions for input Cuprite.

Parameters	240×240	120×120	80×80	60×60
PSNR(dB)	70.5955	70.9262	71.4212	71.523
SSIM	0.9297	0.9698	0.9774	0.9639
SAM	1.5666	1.5663	1.5661	0.9131

Table IV. Comparison between different subdivisions for input Indianpine.

Parameters	240×240	120×120	80×80	60×60
PSNR(dB)	45.4864	45.7911	47.9215	55.757
SSIM	0.9438	0.9446	0.8272	0.8217
SAM	1.5666	1.5649	1.5637	0.4584

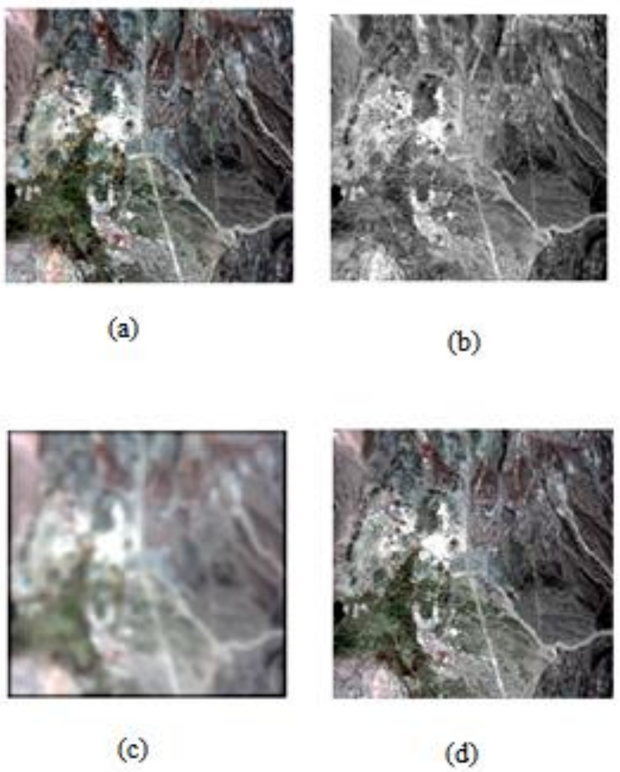

Figure2. (a) The Reference Image, (b)High spatial resolution Multispectral image(c) Low spatial resolution Hyperspectral image (d) The Fusion Output(For Cuprite).

VI. Conclusion

The proposed fusion based super resolution technique reconstructs the HHS image using SU technique. It combines spectral properties of HSI and spatial properties of MSI. The advantage of the proposed fusion method is that it extends the NABO spectral unmixing algorithm to the HSI super resolution. NABO is simpler than VCA. It makes the fusion process faster than the existing methods. The proposed method works in the environment where the spectral-spatial relationships between the inputs are unknown.

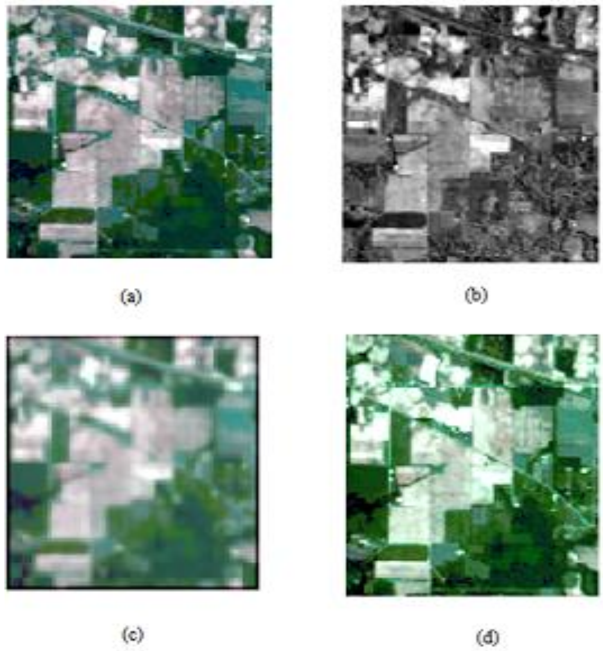

Figure3. (a) The Reference Image, (b)High spatial resolution Multispectral image(c) Low spatial resolution Hyperspectral image (d) The Fusion Output(For Indian Pine).

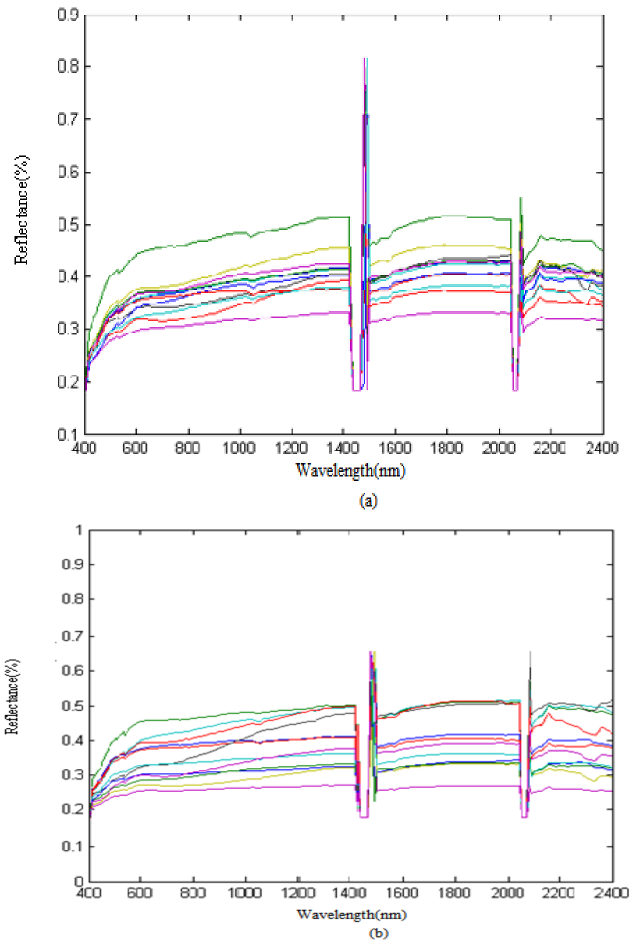

Figure4.Spectral Profile for (a) HSI, (b) Fusion Output. (For Cuprite).

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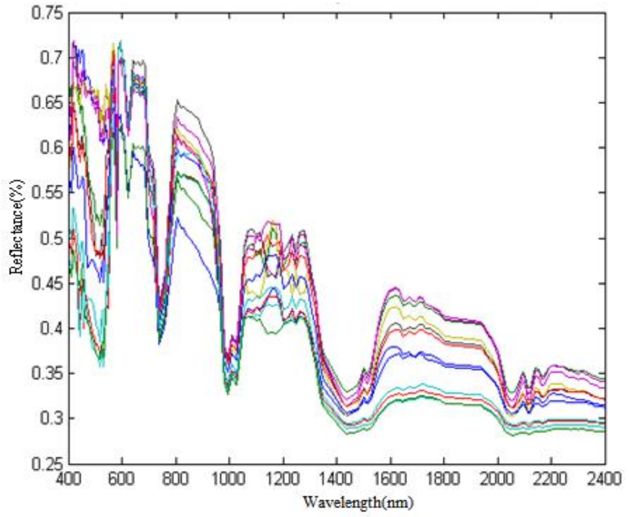
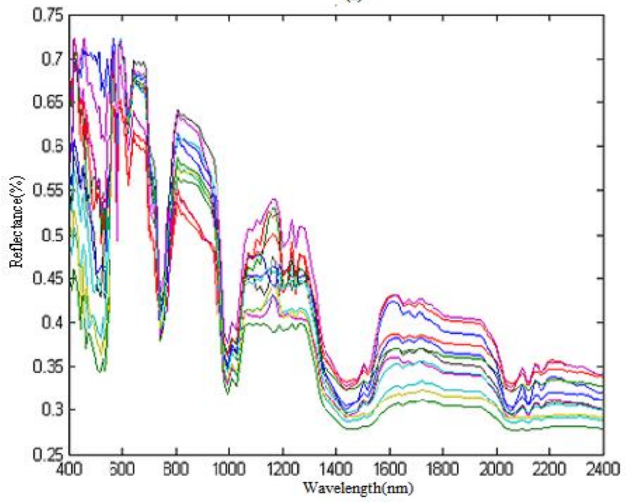


(a)



(b)

Figure5.Spectral Profile for (a) HSI, (b) Fusion Output.(For Indian Pine).

ACKNOWLEDGMENT

We would like to thank reviewers for their valuable and helpful suggestions. We would also like to thank the faculties, the resource providers and the system administrator for the useful feedback and constant support.

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