Multimodal Fusion of Remote Sensing Images

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Abstract--- *In recent years, there has been greater interest in the field of remote sensing, especially in Hyperspectral sensing technology as the information that resides in the HS spectral domain provides significant advantages over the traditional Panchromatic and Multispectral imageries. The inherent tradeoff between the spectral and spatial resolutions has resulted in the development of newer remote sensing systems that include low resolution HS data coupled with high resolution Panchromatic or Multispectral imaging subsystems. In this paper, a novel method called Coupled Non negative Matrix Factorization (CNMF) unmixing based fusion method is used for the fusion of low-spectral-resolution Multispectral data and a low-spatial-resolution Hyperspectral data inorder to produce a fused image data that will be enhanced in terms of its both spatial and spectral qualities which in turn contributes for the accurate identification and classification of various materials in the observed image scene. This algorithm is very straight forward and easy to implement owing to its simple update rules.*

Index Terms--- *Hyperspectral Data, Multispectral Data, Unmixing, Endmember Extraction*

I. INTRODUCTION

IN recent years, Hyperspectral remote sensing technology has been used for increasing knowledge and perception of earth's surface. It is widely used in a variety of real time applications like vegetation mapping, observation of the environment, physics, agriculture and surveillance. The increase in applications is due to the availability of high quality images for an affordable price and with increased computational efficiency. The wealth of information that resides in the spectral domain of the Hyperspectral(HS) image data provides significant advantages over the traditional imaging techniques such as the Panchromatic and Multispectral imageries. However, the design and development of practical HS sensors result in greater tradeoff in its spatial resolution so that important spatial features like texture and shape can be lost. Therefore, the need for higher classification accuracy insists an improvement in the spatial and spectral qualities of remotely sensed imageries. These requirements can be fulfilled by either building new satellites with a higher resolution power, or by making use of a number of image processing techniques. The main advantage of utilizing the image processing techniques for this purpose is their significant low expense. These techniques can be used to establish a tradeoff between the spatial and spectral resolutions by the way of developing a remote sensing systems that includes a low resolution HS data coupled with a high resolution Panchromatic or Multispectral data. Such an image processing technique is referred to as Image Fusion which refers to the process of combining two or more images into a single image such that the resulting image will be more informative than the input images.

A. Types of Remote Sensing Imageries

There are two types of remote sensing imageries available generally**:**

- Hyperspectral Imagery
- Multispectral Imagery

1. Hyperspectral Imagery

Hyperspectral imaging collects and processes information from across the whole electromagnetic spectrum. It divides the image spectrum into many number of bands. This type of dividing images into bands can be extended beyond the visible wavelength range. HS sensors look at image scenes using a vast portion of the electromagnetic spectrum. Certain objects in the scene leave unique 'fingerprints' across the electromagnetic spectrum. These 'fingerprints' are known as spectral signatures which enable accurate identification of materials that make up the observed scene. HS sensors capture information as a set 'images' with each image representing a range of the electromagnetic spectrum known as a spectral band. These images are then combined to form a three dimensional HS data cube for further processing and analysis. The primary advantage of HS imaging is that it makes use of the significance of the spatial relationships among the different spectra in a neighborhood allowing for more accurate segmentation and classification of the image. However, it also has some disadvantages like the design and development of HS imaging sensors is very complex.

2. *Multispectral Imagery*

A multispectral image is one that captures image at specific frequencies across the electromagnetic spectrum. The wavelengths may be separated by filters or by the use of instruments that are sensitive to particular wavelengths. Multispectral imaging divides the spectrum into many bands, which is the opposite of panchromatic imaging which records only the total intensity of radiation falling on each pixel. Satellites usually have three or more radiometers. Each one acquires one digital image in a small band of visible spectra, ranging from 0.7 µm 0.4 µm, called red-green-blue (RGB) region, and infrared wavelengths of 0.7 µm 10 or more µm, classified as near infrared (NIR), middle infrared (MIR) and

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far infrared (FIR or thermal). In the Landsat case, the seven scenes compromise a seven-band multispectral image.

A. Types of Spectral Unmixing

The concept of unmixing assumes that there are two or more spectral signatures are combined within a single pixel in the Field Of View (FOV) of the imaging sensors. The combined spectral signature will be a linear mixture of each spectral component. Linear spectral unmixing is a technique to reveal the subpixel information, such as the number of endmembers in the image scene, endmember spectra, and endmember abundance fractions. There are three basic classification techniques that are used for these purposes namely,

- Unsupervised classification
- Supervised classification
- Hybrid classification

The paper is structured as follows. Section II describes the already existing methodologies for fusion of HS and MS images. Section III deals with the existing methodologies for unmixing HS images. Section IV depicts the description of the work carried out. Section V are concerned with results & discussions for the simulation of a real data set and Section VI ends the paper by presenting some future works to be carried out.

II. Existing Methodologies for Fusion of HS and MS Images

There are three algorithms that are already existing for the fusion of HS Image with a MS Image. They are as follows:

- Wavelet Based Technique
- Maximum Aposteriori Estimation (MAP/SMM)
- Spectral Mixture Analysis Method

A. Wavelet Based Technique

The first algorithm that has been proposed for hyperspectral and multispectral data fusion is awavelet-based technique. This wavelet based technique is based on the pan sharpening algorithm. The performance of the wavelet based technique highly depends on the spectral resampling method, which caused difficulty in enhancing the spatial resolutions of all hyperspectral band images. This is a serious disadvantage of this wavelet based fusion technique.

B. Maximum Aposteriori Estimation (MAP/SMM)

Maximum Aposteriori estimation method was developed to enhance the spatial resolution of HS data using a co-registered high spatial resolution data from an auxiliary sensor. It mainly focused on the use of high-resolution panchromatic data to enhance the spatial quality of HS imagery. This technique is suitable for applications where some correlation exists between the auxiliary image and the image being enhanced. In order to find out these correlations, this technique used a stochastic mixing model (SMM), which estimates the underlying spectral scene characteristics, to develop a cost function that optimizes the estimated HS data relative to the observed HS and MS data. Some of the advantages of this MAP/SMM method are, MAP/SMM method along with wavelet transforms showed a better noise resistance.This approach allows for any number of spectral bands in the primary and auxiliary image. But, the main drawback of this method is that MAP/SMM estimation method is limited to enhancing the low-spatial resolution HS band (225 bands) images only in the MS wavelength regions (0.45 µm to 1.1 µm).

B. Spectral Mixture Analysis

Spectral mixing is an algorithm that estimates the percentage of each endmember within each low resolution multi/hyperspectral pixel. This technique begins with conventional unmixing to generate fractional images. Then, the low spatial resolution HS data are unmixed into its endmember spectra and abundance spectra. Next, the abundances are fused with high spatial-resolution panchromatic data using Constrained optimization(COT) techniques. These Constrained optimization techniques will spatially locate the endmembers to high resolution. Accurate fusion algorithms can be used to integrate spectral and spatial information into a single image presenting the most information to an analyst. The idea of using unmixing for data fusion is physically reasonable and effective for HS and MS data fusion. But, Spectral mixture analysis method does not focus on the estimation of high spatial resolution HS data. Also, this method is suitable for applications where endmembers are known apriori.

III. Existing Methodologies for Unmixing HS Image Data

Hyperspectral unmixing is the decomposition of the pixel spectra into a collection of constituent spectra, and their corresponding fractional abundances that indicates the proportion of each endmember present in the pixel. There are four algorithms that are already existing for the unmixing of HS image data. They are as follows:

- Independent Component Analysis (ICA)
- Pixel Purity Index (PPI)
- Vertex Component Analysis (VCA)

A. Independent Component Analysis (ICA)

ICA is based on two assumptions:1) The observed spectrum vector is a linear mixture of the endmember spectra weighted by the correspondent abundance fractions (sources)2) Sources are statistically independent. Concerning HS data, the first assumption is valid whenever the multiple scattering among the endmembers is negligible. But, the second assumption is not satisfied, since the sum of abundance fractions associated to each pixel is constant. Thus, sources cannot be statistically independent, this compromising the performance of ICA/IFA algorithms in hyperspectral unmixing. However, this method works well even when the endmembers and their spectral signatures are not known apriori.ICA has shown success in many application fields including, blind source separation**,** feature extraction and unsupervised recognition.

B. Pixel Purity Index (PPI)

Pixel Purity Index (PPI) method was developed to extract endmembers from images and to distinct the according endmembers. The PPI algorithm works as a simple technique designed to search for a set of vertices of a convex hull in an L dimensional hyperspectral image cube. The four main steps involved in this unmixing method are as follows:1) Project the raw image cube to its most spectral dimensions and non-noise components by minimum noise fraction (MNF) technology.2) Use the set of spectrally distinct pixels produced by MNF. 3) As skewers for PPI, generates a list of candidates from which final endmembers can be selected. 4) An automatic selection procedure based on K-means clustering is consequently performed to determine the centroid of endmembers. 5) Linear spectral mixing model (LSMM) is used to estimate mixing coefficient. This method involves a time consuming preprocessing step to reduce the dimensionality which makes it ineffective.

C. Vertex Component Analysis (VCA)

Vertex Component Analysis is a new method developed for unsupervised endmember extraction from hyperspectral data. This algorithm exploits two facts namely,1) the endmembers are the vertices of a simplex and 2) the affine transformation of a simplex is also a simplex. VCA works with unprojected and with projected data. As PPI and N-FINDR algorithms, VCA also assumes the presence of pure pixels in the data. The algorithm iteratively projects data onto a direction orthogonal to the subspace spanned by the endmembers already determined. The new endmember signature corresponds to the extreme of the projection. The algorithm iterates until all endmembers are exhausted. This technique reduces the data dimensionality, suppresses undesired spectral signatures, and detects the presence of a spectral signature of interest.VCA performs much better than PPI and better than or comparable to N-FINDR. It has a computational complexity between one and two orders of magnitude lower than N-FINDR.

IV. DESCRIPTION OF THE WORK CARRIED OUT

The design and development of practical high spectral resolution hyperspectral sensors compromise its spatial resolution which results in loss of some essential spatial features like shape, texture, etc. Hence, there is a need to establish a tradeoff between the spectral and spatial resolution of hyperspectral images. The main objective of hyperspectral and multispectral data fusion is to estimate high spatial resolution hyperspectral data from observable low spatial resolution hyperspectral data and high spatial resolution multispectral data. It is assumed the observed two data are obtained under the same atmospheric and illumination conditions. The overview of this project work is to use an unmixing technique called Coupled Nonnegative Matrix Factorization (CNMF) for the fusion of low-spatial-resolution hyperspectral and high-spatial-resolution multispectral data to produce fused data with high spatial and spectral resolutions. Both hyperspectral and multispectral data are alternately unmixed into endmember and abundance matrices by the CNMF algorithm based on a linear spectral mixture model. CNMF is an unsupervised unmixing technique. The CNMF algorithm can produce high-quality fused data both in terms of spatial and spectral domains, which contributes to the accurate identification and classification of materials observed at a high spatial resolution.

A. CNMF Unmixing for HS and MS Data Fusion

The Coupled Non-negative Matrix Factorization (CNMF) unmixing method is applied for fusion of HS and MS images based on linear spectral mixture model. Linear spectral mixture model is widely used for unmixing problems owing to its mathematical simplicity and physical effectiveness. In this model a spectrum at each pixel is assumed to be a linear combination of several endmember spectra and all data are represented in matrix form. Therefore, a fused image data Z is formulated as,

$$Z=WH+N \qquad (4.1)$$

where,

W is the spectral signature matrix with each column vector representing the endmember spectrum

H is the abundance matrix with each column vector denoting the abundance fractions of all endmembers

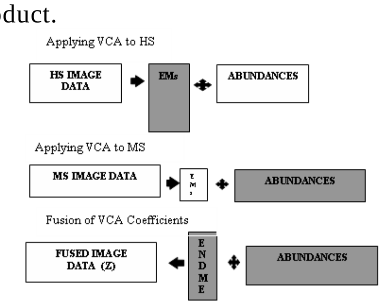
N is the residual

The endmember spectra and abundances are non-negative i.e., W >= 0 and H >= 0. In addition, the sum of the abundances for each pixel can be assumed to be unity.

B. Steps Involved in the CNMF Algorithm

The CNMF alternately unmixes X and Y by NMF to estimate W and H. NMF attempts to decompose a nonnegative data matrix into a product of nonnegative matrices called the endmember matrix and the abundance matrix. The steps involved are as follows:

- Unmix the HS data into its endmember and abundance matrices by applying VCA.
- Unmix the MS data into its endmember and abundance matrices by applying VCA.
- Apply non negative matrix factorization with multiplicative update rule to the VCA coefficients of HS and MS image data alternatively.
- Combine the endmember matrix of HS data and the abundance matrix of MS data by means of taking dot product.



EMs-EndMembers

Figure 1: Block Diagram for CNMF Based Fusion Technique

V. RESULTS AND DISCUSSIONS

a) Data Set Used

Hyperspectral imagery collected by AVIRIS spectrometer, taken over Vaigai River, Madurai, Tamilnadu.

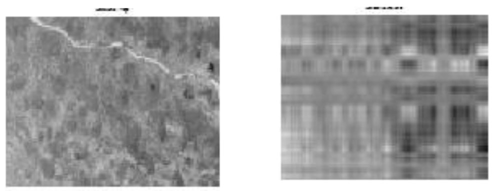


Figure 2: Source Image and its VCA Coefficients of HS Data (Vaigai River, Madurai)

Figure 3: MS Source Image, its VCA Coefficients and CNMF Original Fused Image Respectively (Vaigai River, Madurai)

b) Performance Evaluation

The performance of hyperspectral and multispectral data fusion is evaluated by comparing the finally obtained fused image that is the high spatial resolution hyperspectral data with the original input data in terms of its spatial reconstruction quality. The spatial reconstruction quality is evaluated by means of the peak SNR (PSNR), which is easily defined via the mean square error (MSE). The MSE of the *i*th spectral band image is defines as,

$$\mathrm{MSE}_i = 1/N \sum_{K=1}^{N} (Z - X)^2_{i,k} \tag{4.1}$$

where the index (i, k) indicates the kth pixel in the ith band.

The PSNR of the *i*th band is defined as,

$$\mathrm{PSNR}_i = 10.\log_{10}\left(\frac{\mathrm{MAX}_i}{\mathrm{MSE}_i}\right)^2 \tag{4.2}$$

where, MAX*i* is the maximum pixel value in the *i*th band image. A larger PSNR value indicates a higher quality spatial reconstruction.

c) PSNR Estimated

Table 1: Comparison of Estimated PSNR Values of Source Image Vs. its VCA

No. of Endmembers	HS Source Vs Its VCA (dB)	MS Source Vs Its VCA (dB)
10	20.750	21.134
20	22.042	23.034
30	22.902	24.580
40	23.590	23.590
50	24.185	27.269
60	24.734	28.562
70	25.239	29.862
80	25.717	31.186

Table 2: Comparison of Estimated PSNR Values of Source Image Vs. Fused VCA

No. of Endmembers	HS Source Vs Fused VCA (dB)	MS Source Vs Its VCA (dB)
10	38.666	38.896
20	39.544	40.284
30	40.010	41.081
40	43.303	43.303
50	40.565	41.972
60	40.753	42.228
70	40.917	42.408
80	41.058	42.527

Coupled nonnegative matrix factorization (CNMF) unmixing based fusion technique is used for the fusion of low-spatial-resolution hyperspectral and high-spatial-resolution multispectral data to produce fused data with high spatial and spectral resolutions. The CNMF algorithm is applied for a Hyperspectral and a Multispectral image data individually and their VCA Coefficients are determined which are then fused to get the spatially and spectrally enhanced fused image. Their performance is evaluated in terms of PSNR which is used as the parameter for observing the spatial enhancement of the final fused image. PSNR is computed for Source images Vs. its own VCA coefficients and Source images Vs. fused VCA Coefficients. It is observed that the PSNR value increases as the number of endmembers specified increases.

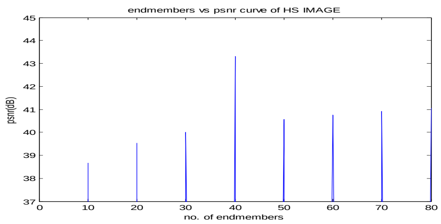


Figure 7: Graph of Endmembers Vs PSNR of Hyperspectral Image – Fused VCA Coefficients

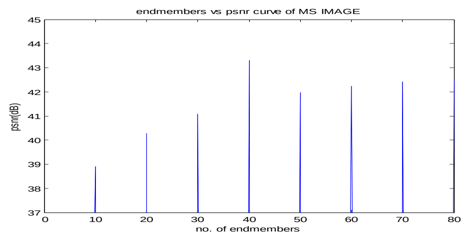


Figure 8: Graph of Endmembers Vs. PSNR of Multispectral Image – Fused VCA Coefficients

VI. FUTURE WORKS

In future, it is planned to apply the same VCA algorithm for various other sets of Hyperspectral-Multispectral image combinations. Also, it is projected to use different fusion techniques like Maximum Absolute Value, Maximum Coefficient Value techniques for fusing the VCA coefficients of Hyperspectral and Multispectral images and to observe their performance evaluation in terms of their PSNR values.

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