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Hyperspectral and Multispectral Image Fusion Techniques

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Abstract*: The hyper spectral image covers a broad range of wavelengths in electromagnetic spectrum, spanning from visible to near-infrared region. The basic objective of hyperspectral imaging is to attain the spectrum for each pixel in the image of a scene, with the aim of identifying objects in the scene and its classification. The hyperspectral images give detailed spectral information but their spatial resolution is very poor. So to enhance the visual quality of the hyperspectral image, we can perform image fusion with high spatial information multispectral image. This paper provides a complete description of hyperspectral imaging and image fusion methods of hyperspectral and multispectral images. A quantitative and qualitative comparative analysis on performance of various hyperspectral and multispectral image fusion techniques are also done.

Keywords: Hyperspectral imaging, Multispectral imaging,pan sharpening.

I. INTRODUCTION

Hyperspectral images (HSI) have wide applications in different areas such as target detection, classification, spectral unmixing, environmental monitoring, agricultural monitoring, forest monitoring, military surveillance, soil type analysis etc. HSI can be mainly characterized by 2 properties, such as spectral resolution and spatial resolution. The spectral resolution represents a number of spectral bands and spatial resolution represents each pixel covers how much earth surface. The spectral resolution of the sensor determines the materials/objects discrimination ability and higher spectral resolution results in better discrimination of objects. Hyperspectral spectrometer acquires a locale in hundreds of continuous spectral bands. However, HS sensors give ample spectral resolution, but spatial resolution is limited. The main aim of hyperspectral image fusion is to improve the spatial resolution using the high spatial resolution multispectral image (MSI).

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Typically, MSIs consist of 3 to 10 noncontiguous (discrete) spectral bands in the electromagnetic spectrum, span across the visible and infrared regions, each band having typically the width of 100 nanometers. An improved version of these early multispectral imaging sensors known as hyperspectral imager provides a spectral width of the order of 10 nanometers for each band. Having very high spectral resolution HSIs can give ample spectral details to recognize and distinguish spectrally distinctive materials in the scene.

II. HYPERSPECTRAL IMAGING

Remote sensing using hyperspectral images is a powerful technology for various applications. The abundant spectral information provides higher discrimination of objects in the scene. The amount of radiation emitted (i.e. radiance), absorbed or reflected, is changing with wavelength for any object. This is the basic idea behind hyperspectral imaging. That is, depending up on the shape, macroscopic scale and molecular composition, the objects in a scene absorb, reflect or scatter the electromagnetic radiation. Hyperspectral sensors collect information in the form of reflectance spectrum in hundreds of contiguous bands (generally with a spectral width of 10 nm) simultaneously in the visible to the mid-infrared portion of the electromagnetic spectrum (0.4-2.5 μm) forming a three dimensional (two spatial dimensions and one spectral dimension) image cube.

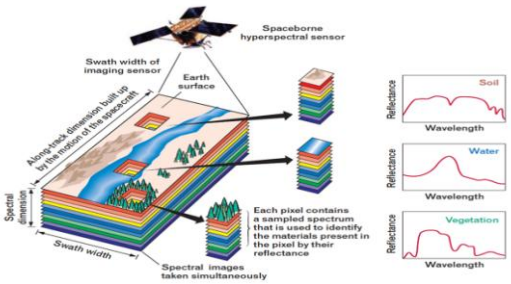

Fig. 1: An illustration of the concept of imaging spectroscopy principle using hyperspectral image cube.

Each pixel in the resulting image is associated with a complete spectral measurement of reflectance, called spectral signature that identifies the object present in the scene. The graphs in figure 1. illustrate the spectral variation in reflectance for soil, water and vegetation.

III. IMAGE RESOLUTION

The hyperspectral imaging spectrometer measures the radiance from a scene through spectral, spatial, radiometric and temporal resolution. The smallest amount of change in a measured value of a physical quantity that an instrument can detect is called resolution.

It is used to quantify the quality of various physical instruments. The high-resolution of an instrument enables us to measure the quantity with better precision. The different types of resolutions are discussed below.

A. Spatial resolution

By using imaging spectrometer, the spectral measurements of various small areas of the earth's surface can be computed, each of which is represented as a pixel in the HIS. The size of the ground area in $metre^2$ represented by a single pixel defines the spatial resolution of an image. Low spatial resolution of a sensor shows blockiness and increases the area covered by one pixel on the earth surface. It leads to an additional challenge to HSI data exploitation because at low spatial resolution, each pixel contains more than one object of the earth surface and it makes the further processing of the data more difficult.

B. Spectral resolution

Spectral resolution defines the capability of the sensor to differentiate between wavelength intervals in bands. Higher the spectral resolution, narrower the range of wavelength for a band. For example, MSIs have bandwidths of 100nm while the widths of HSIs are significantly less and they are of the order of 10nm. This indicates that HSIs can resolve spectral features more effectively than MSIs because of its higher spectral resolution. Based on the spectral response in the narrow bands, high spectral resolution of HSIs facilitates fine discrimination between different materials and objects.

C. Radiometric resolution

The radiometric resolution determines the minute change in the intensity level that can be differentiated by the sensing system by considering the difference the electromagnetic radiation strength. The increase in the brightness resolution requires more number of quantization levels and it increases the number of bits for each level. Most of the multispectral sensors record data up to 8 bits in size, while the hyperspectral sensor such as AVIRIS records data using 12 bits per pixel per band. The consequence of increasing the quantization is the increase in the sensor sensitivity to changes in the reflected signal.

D. Temporal resolution

In order to study the changes over a period of time, sensors should have the capability to capture the image of the same location on earth's surface. By comparing multi-temporal imagery, change in feature's spectral characteristics over time can be detected. Temporal resolution is defined as the time interval between the acquired data of the same location. In remote sensing, this time interval depends on the sensor characteristics and on the orbital characteristics of the sensor platform. The temporal resolution is usually expressed in days and is also depends on the spatial resolution of the sensor. Higher the spatial resolution, lower the temporal resolution.

IV. HYPERSPECTRAL IMAGING SPECTROMETERS

The process of measuring light reflected from a material with respect to wavelength and performing analysis on it is called spectroscopy. Sensors used in hyperspectral imaging are excellent color digital cameras with superior spectral resolution at different illumination wavelengths. These sensors measure the radiation reflected by a pixel region at a large number of invisible or visible frequency bands. The instrument which is used to divides the incident electromagnetic radiation into a number of fine bands and measure the energy in each band is called spectrometer.

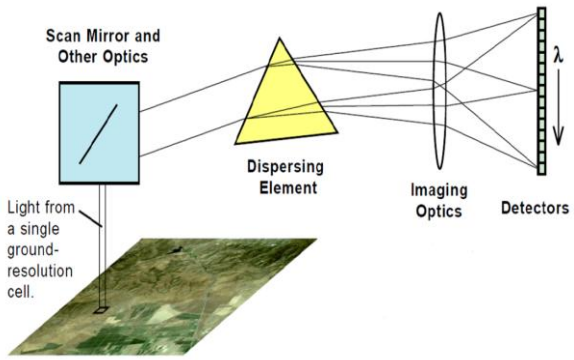

Fig. 2: Components of a spectrometer

Fig. 2 shows the basic elements of an imaging spectrometer. The spectrometers measure the radiation in the region of electromagnetic spectrum dominated by solar illumination $(0.4-2.5\mu m)$. At the absence of sunlight (i.e.,at night) such sensors are ineffective,this problem is tackled by extending hyperspectral imaging into the thermal infrared region $(8-14\mu m)$.At night time materials emit more radiation than they reflect radiation from the sun at daytime, so the sensors can operate effectively during both day and night.

Some common spectrometers are

HYPERION: It gives a high-resolution hyperspectral imager capable of resolving 220 spectral bands from $0.4 to 2.5\mu m$ with a spatial resolution of 30-meter. Complex land eco-systems can be imaged and classified accurately with the help of these spectral bands.

HISUI (Hyperspectral Imager Suite): It is the first satellite mission that used both hyperspectral and multispectral sensors on a single satellite with same spectral coverage of $0.4 to 2.5\mu m$ .It used a multispectral sensor having a spatial resolution of 5-m and a hyperspectral sensor having a spatial resolution of 30-m. It is capable to capture both multispectral and hyperspectral images of the same scene with similar illumination and atmospheric conditions. It is developed by Japanese space agency.

AVIRIS(Airborne visible Infrared Imaging Spectometer): AVIRIS sensor is flawn and maintained by NASA Jet Propulsion Laboratory. AVIRIS images composed of 224 continuous spectral bands with wavelength vaying from $0.4 to 2.5\mu m$. In AVIRIS sensor, Silicon detectors are used for measure visible range wavelength, and indium gallium arsenide for Near Infra Red wavelength.

ROSIS(Reflective Optics System Imaging Spectrometer): This is a closely packed flying imaging spectrometer developed by DLR, the German aerospace centre and operated with DLR's Falcon jet from 1994. It consists of 115 spectral channel having width 4nm in the spectral range of $0.4 to 0.9 \mu m$ with a spatial resolution less than 1 m.

HYDICE(Hyperspectral Digital Imagery Collection Experiment): HYDICE is a well calibrated hyperspectral imaging spectrometer, expected to provide very accurate land cover classifications over large areas. HYDICE collects data of 210 bands over the range $0.4 to 2.5 \mu m$.

V. HYPER SPECTRAL IMAGE FUSION TECHNIQUES

A number of fusion techniques gave been reported in the literature to increase the spatial resolution of HSI with minimal spectral distortion. Pansharpening is a well-established method to improve the spatial resolution of multispectral image by fusing it with a corresponding high spatial resolution panchromatic image. The fusion of hyperspectral and multispectral images varies from pansharpening because both images have spectral and spatial information and fusing panchromatic image with the hyperspectral image will cause spectral distortion because of the different spectral range of sensors.

We can broadly classify the fusion of multispectral and hyperspectral images into 2 categories, such as pansharpening based methods and subspace-based methods. Pansharpening based methods in hyperspectral imagery mainly contain two categories, such as multi-resolution analysis based methods and component substitution based methods. In subspace-based methods, we reduce the dimensionality of hyperspectral data to make the fusion process faster. The subspace-based method also contains two categories, such as matrix factorization based methods and statistical methods. Figure 3 shows the classification of multispectral and hyperspectral image fusion techniques.

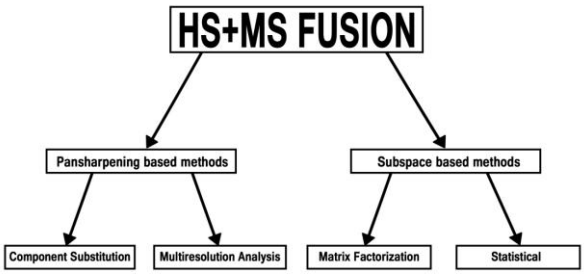

Figure 3: Shows the classification of multispectral an hyperspectral image fusion techniques.

A.Pansharpening based methods

Pansharpening[1] is the fusion of the panchromatic(PAN) and multispectral images to get a high-resolution multispectral image and the resultant image preserves all spatial details of the PAN image. As pansharpening can be considered as a special case of MS-HS fusion problem, so we can generalize the existing pansharpening methods for MS-HS fusion by dividing the set of hyperspectral bands groups and the number of groups is same as that of multispectral bands. Then each group is pansharpened using the corresponding multispectral band.

1. Component Substitution Methods

The first step in component substitution (CS) method is upscaling the size of low-resolution MSI to the size of the PAN image. Using a linear transform of the MS band, MSI is then transformed into a group of components. The CS methods operate by substituting a transformed component of the MSI, C_1 and the PAN image component C_h. The C_1 component should preserve the maximum information content in the MSI for the success of this method. An improper construction of the C_1 component leads to spectral distortion.

The CS based pansharpening techniques is summarized as,

1) Upscale the MS image to the size of the PAN image.
2) Produce forward transform of MS image to get the desired components.
3) Match the histogram of PAN image and the component to be substituted.
4) Replace the C_1 component with the histogram matched PAN image.
5) Applying backward transform the components to obtain the pansharpened image.

The CS family includes many popular pansharpening methods [1], such as the Principal Component Analysis (PCA), Gram-Schmidt (GS) methods and Intensity-Hue-Saturation technique (IHS), and all involve with different transformation of MS image.

2. Multiresolution Analysis

Spatial transforms are usually used to modify or extract the spatial information of remote sensing images. Some of these spatial transforms use only local image information, such as convolution, while others use frequency details, such as Fourier transform. Apart from these two extreme transformations, it is required to represent data to allow the accession over spatial information in a wide range from local to global scales. This method is based on the introduction of spatial information which is obtained through the multiscale decomposition of high spatial resolution PAN image into resampled MSI bands.

Laplacian pyramid (LP) based on multiresolution analysis is a bandpass image decomposition derived from the Gaussian pyramid (GP) and it is a multiresolution image representation obtained through recursive reductions of the image. The algorithm of generalized Laplacian pyramid (GLP)[2] based fusion scheme is,

1) Upsample each MS band to the size of the PAN image.
2) Apply GLP on the PAN image.
3) Select the weights from GLP at each level by considering injection model.
4) Obtain the pansharpened image by the addion of GLP details and each MS band weighted by the coefficients obtained in the previous step.

B.Subspace based methods

In a hyperspectral image, the original spectral features contain high redundancy and also there exists a high correlation between adjacent bands.

So hyperspectral data may active in lower-dimensional subspace. Reduction in dimensionality of hyperspectral data can be accomplished by mapping it to a subspace without losing the original spectral information. The subspace-based methods perform fusion in the subspace and it makes the fusion process faster.

1. Matrix FactorizationMethod

The Nonnegative Matrix Factorization (NMF) model decomposes a nonnegative matrix V, into two nonnegative matrix factors W and H such that,

$$V \approx WH$$

where V denotes the original hyperspectral data, the matrix W represents the endmember matrix contains the spectral vectors of unique materials present in the hyperspectral data and matrix H contains the contribution of individual endmembers to each pixels spectral vector called as abundance matrix. We can improve the spatial resolution of the hyperspectral image by the injection of spatial detail information to abundance matrix H and reconstruct the endmember matrix W by using H. Spatial and spectral information of an image can be preserved by using matrix factorization with a medium computational cost.

N. Yokoya et al [3] developed a method based on Coupled nonnegative matrix factorization (CNMF) unmixing to fuse hyperspectral image with multispectral image. The fused images have the spatial resolution of input MSI spectral resolution of input HSI. In which, nonnegative matrix factorization is used to alternately unmix the two input images into endmember matrix and their abundance. To make the unmixing process easier, forward models related to two sensors are used**.**

2. Statistical methods

a) Maximum a posteriori(MAP) estimation

R. C. Hardie et al.[4] proposed a maximum a posteriori(MAP) estimator for improving the spatial resolution of HSI using co-registered high spatial-resolution imagery from an auxiliary sensor. It focuses on improving hyperspectral imagery using high-resolution panchromatic data. The estimation framework allows any number of spectral bands in primary and auxiliary images. This method exploits the local or global correlations between the two input images. A spatially varying statistical model based on vector quantization is used to exploit localized correlations,. The forward model in MAP can be represented as follows:

$$y = Wz + n \qquad (1)$$

Here z denotes the image with enhanced resolution, y denotes HSI with low spatial resolution and n is the spatially independent zero mean gaussian noise with covariance matrix C_n .The high spatial resolution MSI is modeled as,

$$x = S^T z + n \qquad (2)$$

where S is the spectral response matrix, x is the high spatial resolution multispectral image and n is the spatially independent zero-mean gaussian noise with covariance matrix C_n.

Maximum a posteriori (MAP) estimator is a method used to get an estimate for the high spatial resolution HSI, that maximizes conditional probability depends on the two observations. It is given by,

$$\hat{Z} = \arg\max_z \; p(z \mid y, x) \qquad (3)$$

Using Bayes theorem and assumption that, the two input images are independent, we can write the above equation as,

$$\hat{Z} = \arg\max_z \; p(z \mid y, x)\, p(z \mid x) \qquad (4)$$

Instead of maximizing the above function, we can minimize the exponential terms in the probability density functions conditional probabilities.

b) Wavelet based Bayesian fusion

Y. Zhang et al.[5] presented a method to fuse hyperspectral and multispectral images to improve the spatial resolution of HSI in wavelet domain. It is almost similar to maximum a posteriori (MAP) estimation discussed earlier, the only difference here is applying estimation in the wavelet domain. Two main motivations for estimation in wavelet domain is,

- Wavelet transform spatially decorrelates the pixels, for allowing accurate and simplified modeling.
- Wavelet transform provides a scale-specific estimation of the model parameters so that the fusion of the multispectral and hyperspectral images is done in a controlled manner.

In this method, the wavelet transform prior to MAP estimation is done. Each band of input hyperspectral image is wavelet transformed, for each decomposition (resolution) level and each orientation, a detail image is generated. Then MAP estimation in the wavelet domain is performed. The wavelet transform represents the image details in a compact way. The detail images are sparse matrices with a small number of large coefficients representing the edges. This provides the distinction between real image information and noise. So denoising is superior in the wavelet domain.

c) Bayesian fusion based on sparse prior

The fusion of high spatial resolution MSI and low spatial resolution HSI is formulated in the Bayesian inference framework. Q. Wei, et al.[6][7] pu forwarded the Bayesian fusion technique for multi-band images. The given high spectral and high spatial resolution images are to be recovered from degradations such as spectral blurring, spatial blurring, and downsampling based on the sensor characteristics. The problem is framed as an ill-posed inverse problem. It requires prior information about the image to be reconstructed to make the problem well-posed. In this work, they used a sparse prior to regularize the ill-posed inverse problem. Initially, compute a rough estimate of the high-resolution hyperspectral image using Maximum Aposteriori (MAP) estimation. The sparsity-based prior consist of learning dictionary and the associated sparse coefficient matrix on each band of the rough estimate. Finally, solve the ill-posed inverse problem using alternate optimization based on the target image and sparse coefficients matrix to get the high resolution HSI.

Result by [4]

Result by [5]

Result by [3]

Figure 4: Comparison of hyperspectral and multispectral Image Fusion methods.

The performance of three important hyperspectral and Multispectral fusion methods in [4], [5] , [3] are compared qualitatively and quantitatively. The quantitative evaluation is done with Root mean square error (RMSE), Spectral angle mapper (SAM), Universal Image qualitity index (UIQI), Relative Dimensionless Global Error in Synthesis (ERGAS) and Degree of Distortion (DD). Table 1 shows the quantitative performance comparison with these metrics. Figure 3 shows the results after applying different methods.

TABLE I
Performance Comparison

Methods	RMSE	UIQI	SAM	ERGAS	DD
MAP	2.591	0.9578	4.591	3.112	1.821
Wavelet MAP	2.158	0.9693	3.821	2.581	1.511
CNMF	2.221	0.967	3.89	2.659	1.531

VI. CONCLUSION

Hyperspectral images are extensively used in different applications such as target detection, classification, spectral unmixing, environmental monitoring, agricultural monitoring, forest monitoring, military surveillance, soil type analysis etc as it contains detailed information. Fusion techniques are used to improve the quality of hyperspectral images. This paper described in detail about hyperspectral imaging. A review on different hyperspectral and multispectral image fusion methods are done. Performance of these methods is compared quantitatively and qualitatively.

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