



INTERNATIONAL JOURNAL OF PURE AND APPLIED RESEARCH IN ENGINEERING AND TECHNOLOGY

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FUSION OF MULTISPECTRAL AND HYPERSPECTRAL IMAGES USING PCA AND UNMIXING TECHNIQUE

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Accepted Date: 15/03/2016; Published Date: 01/05/2016

Abstract: In remote sensing due to the cost and complexity multispectral and hyper spectral sensors have significantly lower spatial resolution than panchromatic images. The spectral and spatial resolutions are somewhat complementary. More specifically, HS images have lower spatial resolution than MS images, due to the high spectral resolution of the former. HS images typically have 100–210 spectral reflectance bands, whereas MS images have four to eight bands. The proposed method for fusion of MS and HS and PAN images and of MS and HS images. MS and, more so, HS images contain spectral redundancy. Using proposed method the images should be clear than the original images. It gives more information than the original images. The proposed method preserves the spatial and spectral information. In unmixing technique high frequency is removed and the proposed method gives us high spatial hyper spectral data.

Keywords: Image Fusion, Principal Component Analysis (PCA), Unmixing Technique



PAPER-QR CODE

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Access Online On:

www.ijpret.com

How to Cite This Article:

R. A. Deshmukh, IJPRET, 2016; Volume 4 (9): 595-603

INTRODUCTION

Remote sensing is a rapidly evolving field, and during the last decades, air- and space borne imaging sensors have seen a steady improvement in both the spatial and spectral resolutions of the acquired imagery. Because of both the complexity of the sensors and cost issues, the spatial resolution of multispectral (MS) and hyper spectral (HS) sensors is considerably lower than for a single-channel sensor, i.e., panchromatic sensor. Since a typical Earth imaging satellite has both MS and PAN sensors mounted on the same platform, these images are simultaneously acquired such that both images show the same consequently, there is no need to co register MS and PAN imagery. To make the most of the available data, the MS image is typically enhanced using the PAN image such that the resulting MS image has the same spatial resolution as the PAN image. This process of fusing the MS and PAN images is called pansharpening. The pansharpened image should, ideally, have the spectral resolution of the MS image and the spatial resolution of the PAN image. Today, pansharpening is an important technique and is used to produce the imagery seen in the popular Google Maps/Earth and Microsoft Bing Maps products. There are also several applications within the field of remote sensing that benefit from pansharpened imagery, e.g., change detection and classification panchromatic (PAN) sensor.

While many pansharpening methods have been proposed, most of the methods belong to two classes or families. These are the so-called component substitution (CS) and multi resolution analysis (MRA) families. The CS family is typically based on replacing a component acquired through some spectral transformation of the MS image with the PAN image and subsequently applying the inverse transform to obtain the fused image.

As current satellite system provide hyper spectral(HS) and multispectral (MS)image, there is need to improve image fusion by using HS and MS. Hyper spectral satellite images with precise spectral information allow for accurate analyses of terrestrial features. However, these images generally have coarser spatial resolutions than do panchromatic and multispectral images because of the tradeoff between spectral and spatial information in sensor design.

I. Background

The block based algorithm generates a simulated multispectral band via a spectral unmixing technique and extracts high-frequency information based on blocks of associated bands. This algorithm contain two phases simulation phase and fusion phase [1]. ARSIS method is used to the multispectral images fusion. For the global quality assessment of the resulting fusion image from each method, compared them with a reference image, by means of statistical parameters

such as the relative absolute squared error (RASE), the relative a dimensional global error in synthesis (ERGAS), the spectral angle mapper (SAM), the correlation coefficient (CC), the standard deviation (SD), the relative bias (RB), and the universal image quality index (UIQI) [2]. The use of satellite imagery to support agricultural applications has been recognized since the 1970s. However, inadequate spatial and spectral resolutions as well as insufficient revisiting frequencies have largely impaired the use of satellite sensors for crop management. Recently, some studies have shown that hyperspectral systems can be mounted on unmanned aerial vehicles (UAVs). The hyperspectral mapping system (HYMSY) developed at Washington University under the Smart Inspectors project is one such example. Flexible image acquisition dates and user-controlled spatial resolution as well as flight paths are the benefits of such a system [3]. More recently, hyperspectral (HS) imaging acquiring a scene in several hundreds of contiguous spectral bands has opened a new range of relevant applications such as target detection and spectral unmixing. However, while HS sensors provide abundant spectral information, their spatial resolution is generally more limited. To obtain images with good spectral and spatial resolutions, the remote sensing community has been devoting increasing research efforts to the problem of fusing HS with MS or PAN images. From an application point of view, this problem is also important, as motivated by recent national programs, e.g., the next-generation space borne HS image suite, which fuses coregistered MS and HS images acquired over the same scene under the same conditions [4]. A novel algorithm for the fusion of the HMS image and the LHS image to enhance the spatial resolution of the latter with relatively small spectral distortion is proposed. In the introduced algorithm, both HS and MS images are unmixed via LMM, by taking the sensor observation models into consideration to match the unmixing outputs [5].

This paper is organized as follows. Sectional introduction, section II discuss background, section III discuss previous work done, section IV discuss existing methodology, section V discuss attribute and parameter and how they affect, section VI proposed method section VII possible result and outcomes finally section VIII conclude this paper.

II. Previous work done:

The block based algorithm for fusion consists of two parts. The first part consists of a simulation phase that is used to generate a simulated multispectral band (SMSB) using the spectral unmixing technique and spectral adjustment. The original CNMF process is considered to obtain high-quality spectral and spatial information. The second part is the fusion phase, which includes block-based image fusion based on the association of the hyperspectral and

multispectral bands [1]. The existing pan-sharpening method named ARSIS to the multispectral images fusion is adopted. For the global quality assessment of the resulting fusion image from each method, compared them with a reference image, by means of statistical parameters such as the relative absolute squared error (RASE), the relative a dimensional global error in synthesis (ERGAS), the spectral angle mapper (SAM), the correlation coefficient (CC), the standard deviation (SD), the relative bias (RB), and the universal image quality index (UIQI) [2]. New methodology to obtain STRS based on Bayesian theory, which allows the uncertainties to be quantified. First, the multispectral reflectance spectra are imputed to the hyperspectral intervals based on the a prior covariance between spectral bands of similar signatures, in which pansharpening is occur [3]. There is fusion of HS and MS images within a constrained optimization framework, by incorporating a sparse regularization using dictionaries learned from the observed images. Knowing the trained dictionaries and the corresponding supports of the codes circumvents the difficulties inherent to the sparse coding step. The optimization problem can be then solved by optimizing alternatively with respect to (w.r.t.) the projected target image and the sparse code. The optimization w.r.t. the image is achieved by the split augmented Lagrangian shrinkage algorithm (SALSA), which is an instance of the alternating direction method of multipliers (ADMM). By a suitable choice of variable splittings, SALSA enables a huge non diagonalizable quadratic problem to be decomposed into a sequence of convolutions and pixel decoupled problems, which can be solved efficiently [4]. Similarly to the CNMF method, the proposed algorithm also requires the knowledge of both sensor observation models. Finally, the spatial and spectral performances of the unmixing fusion based approach algorithms are verified and evaluated by comparing it with the CNMF and MAP-SMM algorithms [5].

III. Existing methodology

Block-Based Fusion Algorithm with Simulated Band Generation for Hyperspectral and Multispectral Images of Partially Different Wavelength Ranges in this unmixing and block based techniques are used. In this two phases are used and that are simulation phase and fusion phase. The algorithm generates a simulated multispectral band via a spectral unmixing technique and extracts high-frequency information based on blocks of associated bands [1]. The concept of multiresolution was introduced by Mallat. This mathematical tool allows to calculate successive approximations of one image from high to coarse resolution. It can be schematized by a Laplacian pyramid. The difference of information between two approximations is modeled by the wavelet coefficients obtained from the wavelet transform. The wavelet transform can be replaced by the filter banks for instance. These operations are invertible and then, from an

approximation of the original image and with the wavelet coefficients, it is possible to reconstruct the original image without any loss of information. The ARSIS concept implementation (from its French acronym Amélioration de la Résolution Spatial par Injection de Structures) is a pan-sharpening method based on the assumption that the missing information of the low-resolution multispectral image can be provided by the high spatial frequencies of a higher resolution panchromatic image [2]. The new methodology to obtain STRS based on Bayesian theory, which allows the uncertainties to be quantified. First, the multispectral reflectance spectra are imputed to the hyperspectral intervals based on the a priori covariance between spectral bands of similar signatures [3]. The fusion problem is formulated as an inverse problem whose solution is the target image assumed to live in a lower dimensional subspace. A sparse regularization term is carefully designed, relying on a decomposition of the scene on a set of dictionaries. The dictionary atoms and the supports of the corresponding active coding coefficients are learned from the observed images. Then, conditionally on these dictionaries and supports, the fusion problem is solved via alternating optimization with respect to the target image (using the alternating direction method of multipliers) and the coding coefficients [4]. The number of end members extracted from the MS image cannot exceed the number of bands in least-squares-based spectral unmixing algorithm, large reconstruction errors will occur for the HSI, which degrades the fusion performance of the enhanced HSI. Therefore, in this paper, a novel fusion framework is also proposed by dividing the whole image into several sub images, based on which the performance of the proposed spectral unmixing based fusion algorithm can be further improved [5].

IV. Analysis and discussion

Block based fusion algorithm was tested using CASI airborne hyperspectral images with various spatial and spectral resolutions. The CASI images used in this study were taken from Gangnaemyeon, Cheongwon-gun, and Chungcheong buk-do, Korea, and were captured at an altitude of 750 m on June 22, 2013. The time interval between the imaging in the two modes was less than 10 min. The radiance values of the collected CASI images were converted to reflectance values, and image registration and empirical calibration between the images were performed in two modes. Noise bands were removed from the collected images; a total of 90 bands in mode 1 and 45 bands in mode 2 were used [1]. The concept of multiresolution was introduced by Mallat. This mathematical tool allows to calculate successive approximations of one image from high to coarse resolution. It can be schematized by a Laplacian pyramid. The difference of information between two approximations is modeled by the wavelet coefficients obtained from the wavelet transform. The wavelet transform can be replaced by the filter banks for instance.

These operations are invertible and then, from an approximation of the original image and with the wavelet coefficients, it is possible to reconstruct the original image without any loss of information [2]. The two-step method retains the traditional spectral characteristics of vegetation. However, the temporal spline interpolation causes spectra to change rapidly in short time periods. For example, the Formosat-2 reflectance factors on July 8th and July 18th are lower than the UAV reflectance factors on July 5th and July 17th, respectively. The sharp decrease between the UAV and subsequent Formosat-2 observations causes the two peaks in green reflectance (~560 nm) at these dates. In contrast, the new Bayesian STRS methodology presents realistic daily spectra with smoother temporal changes [3]. A high spectral low spatial resolution HS image has been constructed by applying a 5 × 5 Gaussian spatial filter on each band of the reference image and down-sampling every four pixels in both horizontal and vertical directions. In a second step, we have generated a four-band MS image by filtering the reference image with the IKONOSlike reflectance spectral responses. The HS and MS images are both contaminated by zero-mean additive Gaussian noises [4]. The scene is taken over the Washington DC Mall by the Hyperspectral Digital Imagery Collection Experiment (HYDICE) sensor containing 240 × 240 pixels with 191 spectral bands ranging from 400 to 2500 nm. The second scene is taken over the Indian Pine by the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) sensor, containing 120 × 120 pixels with 224 spectral bands in the 400–2500-nm region; author use only 204 spectral bands after removing the bands covering the water absorption region: 104–108, 150–163, and 220 [5].

Methodologies	Advantages	Disadvantages
Block based fusion algorithm	The block-based fusion preserved more spectral information of features, such as trees, paddy fields, and roof top, and it improved the spatial detail	This algorithm was limited to hyperspectral fusion using multispectral images.
ARSIS	ARSIS is better adapted to water applications because it promotes MERIS information compared with the ETM information and then better	High dependency of spatial and spectral complexity of landscapes.

restores the water diversity.

It maintain consistency.

STRS based on Bayesian approach	Accurately combining HS and MS data in spectral and temporal dimension	Insufficient sensors, did not provide surface reflectance data at spectral and temporal interval defined by user
HS and MS image fusion based on sparse representation	Offered smaller spatial error and smaller spectral distortion	Selection of regularized parameter is big issue
Spectral unmixing	It is easy to implement as well as parallel implementation can be possible.	spectral relationship between the observed HMS image and the estimated HHS image is unknown.

V. Proposed methodology

Observation model:

The method is based on observation model

$$Y = WZ + N_1 \dots \dots \dots (1)$$

Where Y is spatially up sampled N * P observed low resolution HS image with P spectral reflectance bands of N pixel each. W is the spatial degradation operator. N₁ is the zero mean Gaussian noise.

UDWT of the model:

The wavelet transform decomposes an image into a low pass and high pass detail bands at different resolution scales and orientation.

$$B = WG + N \dots \dots \dots (2)$$

Where B and G are UDWT coefficients of loadings of B and G respectively. N is the Gaussian noise.

The main motivation of this model is that it reduce the spatial correlation of pixels simplifying the estimation and more robust.

The reason for this is that the low level contains an approximation of the signal itself and this band has in general a nonzero mean, whereas zero mean detail bands contain deviation at various resolution level.

Linear spectral mixing model:

The linear mixing model(LMM) has been widely utilized to model the remote sensing data, which implies that the mixed pixel are represented as linear combinations of endmember for high resolution hyperspectral image Z the LMM is denoted as follows:

$$Z = SA + N_z \dots \dots \dots (3)$$

Where S is p*d (d is number of endmembers). A is d*n fractional abundance matrix and N_z is p*n noise matrix.

Unmixing based fusion:

The endmember of hyperspectral image is made up. Simulation of endmember and multispectral is occurred and from that high frequency is removed and we get the fusion of hyperspectral and multispectral image.

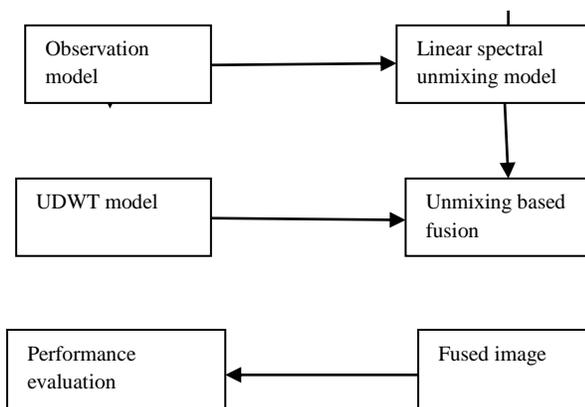


Fig: workflow of proposed method

VI. Possible result and outcomes

Result must be better than observational model using for images. It should be more clear than the original hyperspectral and multispectral image. It gives more information than the original image coz when fusion of two or more images occur it gives more data. It should preserve the spectral and spatial information.

VII. CONCLUSION

The proposed method use the observation model after that is has two ways of fusion and that is by UDWT model or by unmixing technique. The UDWT decomposes an image into into a low pass approximation and high pass detail bands. In unmixing technique extracts high-frequency information based on blocks of associated bands. Both approaches gives us more information than the original images. The proposed method preserves more spatial and spectral information.

FUTURE SCOPE

This method has big future scope in remote sensing, food processing as well as mineralogy.

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