ISSN: 2321- 8169
259 - 263

Image Fusion and Recursive Filtering based Feature Extraction of the Hyperspectral Images

Aarti Jagdish Chorghe
Master of Technology, Student
K J Somaiya College of Engineering, Mumbai, India
Department of Electronics and Telecommunication
chorgheaarti@gmail.com

Abstract - Hyperspectral images obtained from hyperspectral satellite sensors have high resolution. This is because these images have several spectral bands for every pixel and hence they provide detailed information regarding the physical nature of the different materials. However, due to high dimensionality of hyperspectral data, a problem named as "Hughes phenomenon" arises. For such cases feature extraction is an effective way in reducing the dimensionality. Various feature selection and feature extraction methods are discussed. This paper deals with a simple method based on image fusion and recursive filtering (IFRF) to extract the features of the hyperspectral images. Firstly, the hyperspectral image is partitioned into multiple subsets of adjacent bands. These bands are then fused together by using the simplest fusion technique i.e. averaging. Lastly, the fused bands are processed with the transform domain recursive filtering to get the resulting IFRF features for classification.

Keyword: Hyperspectral image, feature extraction, image fusion(IF), recursive filtering(RF)

I. INTRODUCTION

Hyperspectral remote sensing is one of the most advanced technology and one of the most significant breakthroughs in remote sensing. It has emerged as a promising technology for studying earth's surface spectrally and spatially. Hyperspectral data consists of hundreds of spectral bands with a high spectral resolution. This enables acquisition of continuous spectral characteristics and therefore serves as a powerful tool for vegetation classification. Hyperspectral imaging combines the power of digital imaging and spectroscopy. For each pixel in an image, a hyperspectral camera acquires the light intensity (radiance) for a large number (typically a few tens to several hundred) of contiguous spectral bands. Every pixel in the image thus contains a continuous spectrum in radiance or reflectance and can be used to characterize the objects in the scene with great precision and detail. If the objects of representation are the pixels in an image, a hyperspectral image can be modelled with a Euclidean space, where the number of bands is the dimension of the space and the pixels in the image are represented as points in that space. However, to incorporate efficient methods to process these images with more number of bands becomes a difficult objective. For hyperspectral images, several hundreds of spectral bands of the same scene are typically available. By increasing the dimensionality of the images in the spectral domain, theoretical and practical problems arise. For instance, with a limited training set, beyond a certain limit, the classification accuracy actually decreases as the number of features increases [1]. For the purpose of classification, these problems are related to the curse of dimensionality. Also with high dimensionality the problem of "Hughes phenomenon" arises. This influences the classification performance [1]. In order to solve these problems techniques such as feature extraction and feature selection can be used for hyperspectral image classification. A feature is any aspect, quality or characteristic of an object. Feature selection focuses on the best subset of spectral bands that provide highest class separability [2]. It preserves the physical meaning of data. Spatial information preservation is important for feature selection in case of hyperspectral images. Feature extraction is the process by which certain features of interest within an image are detected and represented for further processing. It focuses on reducing the amount of resources required to describe large set of data correctly. This is an effective way to reduce the dimensionality of the data. Feature extraction aims to process the image in such a way that the properties of it can be adequately represented in compact form. Different methods to reduce the dimensionality can be used.

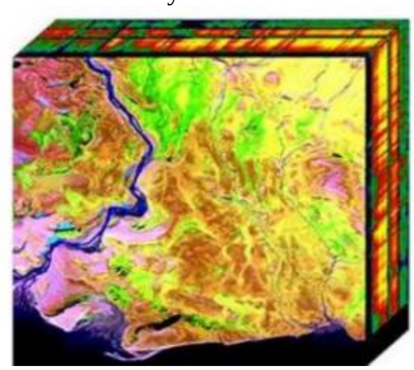

Figure 1: 2-D projection of hyperspectral cube

Hyperspectral sensors record the reflectance from the earth's surface over the full range of solar wavelengths with high spectral resolution. The resulting high dimensional data contains rich information for a wide range of applications. However, for a specific application not all the measurements are important and useful. The original feature space may not be the most effective space for representing the data. Given that the spectral reflectance of most materials changes only gradually over certain spectral regions, many contiguous bands are highly correlated, resulting in redundant measurements. Noisy bands are associated with regular water absorption features around 1400 and 1900 nm, as well as instrument noise and transient externalities. More importantly, while the data of the complete set of hundreds of spectral bands provide opportunities for a wide range of applications, they are not designed for any particular problem. Each band may or may not reveal unique absorption features of the materials of interest in a given problem. Thus, a given band can be a useful feature for one problem, but not for another. Therefore, the original hyperspectral bands are essentially candidate features for a specific application. Identifying effective features to model the characteristics of classes represented in the data is a critical preprocessing step required to render a classifier's effectiveness in hyperspectral image classification [3]. So feature selection focuses on finding the best subset of hyperspectral bands that provide the highest class separability. There are different methods that are proposed for the same. Kuo and Landgrebe [4] proposed a hyperspectral data processing chain where feature reduction was emphasized as an important data pre-processing stage consisting of both feature selection and feature extraction. The former process identifies the best subset of features from all the candidate features based on an adopted selection criterion. Lorenzo Bruzzone [5] emphasizes on preservation of spatial information for feature selection. This is done by defining two terms. One to measure the class separability and the other to evaluate spatial invariance of selected feature. This results in more robust classification and increases generalisation capability. As mentioned, feature selection aims at finding the best subset of hyperspectral bands but practically they can be found out only by performing exhaustive search for all the feature subset combinations. This is a time consuming task because as the dimension increases the number of possible combinations goes on increasing exponentially.

The other method to reduce the dimensionality of the data is feature extraction. A hyperspectral image is first transformed into another feature space by applying a linear transformation and then is subjected for classification. There are different dimensionality reduction techniques which can be classified as unsupervised and supervised techniques. Examples of unsupervised techniques are PCA and ICA and that of supervised approaches include linear discriminant analysis. PCA is a powerful tool for analysing data. PCA makes sure that most of the information of the hyperspectral image can be preserved into small amount of significant principal components. PCA is mainly concerned with identifying the correlations in the data. The main advantage of PCA is by reducing the dimensionality, the loss of information is not much. The drawback of PCA is it cannot ensure that the spectral signatures are emphasized. ICA ensures the transformed components are as independent as possible. It doesn't consider the spatial context information. Also it has certain ambiguities like components are not ranked as in PCA and they are extracted randomly. ICA is computationally expensive too.

To improve the classification performance many researchers have worked on spectral–spatial classification which can incorporate the spatial contextual information into the pixelwise classifiers. This type of classification can incorporate spatial contextual information i.e. it can retain strong relationship between neighbouring pixels. Few of the spectral-spatial classification methods focus on preprocessing the classification map obtained according to the spatial structures [6]. For such methods segmentation and optimization techniques give better results. A hyperspectral image is first segmented into different regions based on the homogeneity of either intensity or texture [7] so that all the pixels within the same region can be considered as a spatial neighbourhood. Different hyperspectral segmentation techniques such as partitional clustering, watershed, hierarchical segmentation, and minimum spanning forest can be used for this objective. But these techniques are found to be very time consuming. A solution to this problem is to incorporate the spatial information in the feature extraction process itself. In recent researches many methods have been proposed for the same. Benediktsson [8] proposed a transform to model the spatial structures in hyperspectral images. First PCA is performed on original hyperspectral image to obtain the principal components. Then these components are processed to model spatial structures of different scales. Zhang [9] proposed that hyperspectral data can be represented using tensor representation to make full use of spatial information. All these mentioned studies have verified that the classification accuracy can be improved by combining spectral and spatial information in the feature extraction process. Edge preserving filtering has found applications in dynamic imaging, stereo matching, image fusion [10], dehazing and denoising. This is because it can smooth an image while preserving its edge structure well. An edge-reserving filtering based spectral-spatial classification method is proposed in [11]. According to [11], a hyperspectral image is first classified using a pixelwise classifier. Then the classification map is represented as multiple probability map and edge-preserving filtering is performed on every map. According to the filtered probability maps, class of each pixel is selected based on maximum probability. There are different edge-preserving filtering techniques like joint bilateral filters, weighted least square filters, guided filter and domain transform filter [12].

II. Image Fusion and Recursive Filtering Based on Feature Extraction Method

Hyperspectral images are high resolution images which are available with hyperspectral satellite sensors. They provide spectral information with high resolution. Therefore they can be used to distinguish between different landscapes. Hyperspectral images have hundreds of spectral bands with a very good spectral resolution. This enables acquisition of continuous spectral characteristics. Xudong Kang [13] proposes that the feature extraction of a hyperspectral image is done by partitioning it into subsets of adjacent bands which are then fused together by using the most basic fusion technique i.e. average fusion. Recursive filtering is performed on the fused bands and given to the classifier (SVM) for classification. This improves the classification accuracy [13]. Two important assumptions are made in [13] which are adjacent bands of hyperspectral image contains redundant information and the neighboring pixels have strong correlations with each other. Because of the first assumption, image fusion is used. Recursive filtering is used to ensure that the spatial context information is utilized in the feature extraction process.

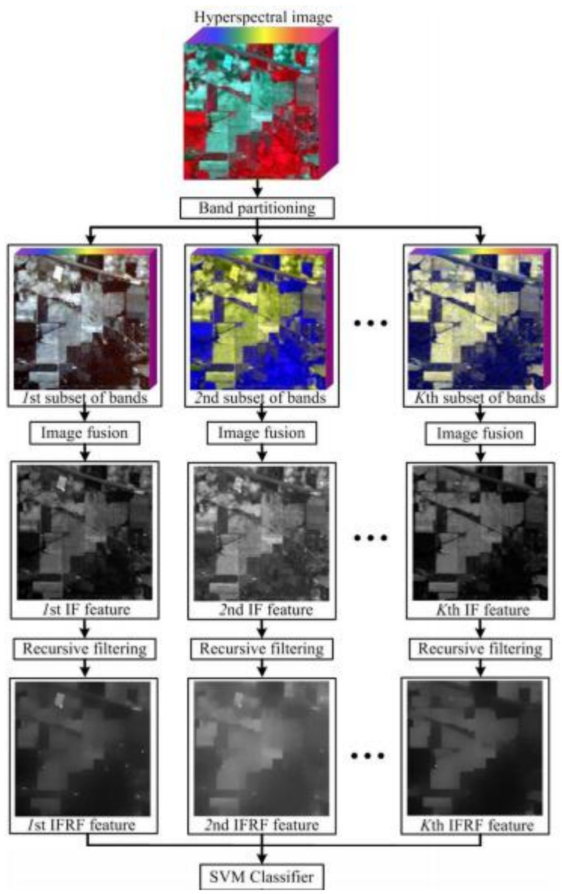

Figure 2: Schematic of IFRF based feature extraction method

A. Band Partitioning

Satellite images captured by hyperspectral sensors have more than 100 spectral bands for every pixel. Therefore hyperspectral image provides detailed information along with very high spectral resolution. But processing these many bands becomes a difficult task during classification. Therefore, the hyperspectral image is partitioned into K subsets of

hyperspectral bands. The k^{th} subset $(k \in (1,.......K))$ can be obtained as follows [19]:

$$p^k = \begin{cases} \left(x_k, \dots\dots\dots x_{(k+[D/K])}\right) & if\,(k + [D/_k]) \leq D \\ \left(x_{k,}......................x_D\right) & (k + [D/_k]) > D \end{cases} \tag{1}$$

where $x=(x_1,...........x_D)$ denotes the original hyperspectral image with D-dimensional feature vectors and [D/K] represents the flooring operation. This calculates the largest integer which is not greater than D/K.

B. Image Fusion

Image fusion is the procedure of fusing two or more images of same scene to form a single fused image which displays vital information. It is the means of using the data to improve the quality of information. Image fusion gives sharper resolution and improves the classification. The increasing availability of space borne sensors gives motivation for different image fusion algorithms. Image fusion allows integration of different information sources. Image fusion can take place at 3 levels: pixel, feature extraction, decision [14]. There are many methods to incorporate image fusion. Image fusion methods are broadly classified into two groups: spatial domain fusion and transform domain fusion [14]. Spatial domain fusion techniques include average fusion, PCA, IHS, HPF based technique. Transform domain fusion techniques like discrete wavelet transform, discrete cosine transform, stationary wavelet transform are also used for image fusion. Many applications in image processing require high spatial and high spectral information in a single image. With respect to hyperspectral images, image fusion is used to combine the complementary information of the adjacent bands for feature reduction. Image fusion has many advantages like it effectively removes noise, preserves the structural information in fused bands well.

The image fusion method used in[13] is the simplest image fusion technique i.e. the averaging method. In this method the adjacent bands in the k^{th} subset are fused. The k^{th} fused band is calculated as,

$$Q^k = \frac{\sum_{n=1}^{N_k} P_n^k}{N_k} \tag{2}$$

where P_n^k refers to n^{th} band of k^{th} subset of hyperspectral bands and N_k refers to total number of bands in k^{th} subset. It calculates average image of each subset and removes noise and redundant information of each subset i.e. spectral redundancy is taken care of.

C. Edge Preserving Filters

Edge-preserving filters are used for joint filtering where the content of one image is smoothed based on the edge information. There are many different EPFs [11] e.g. the joint bilateral filter, weighted least square filter, guided filter, the domain transform filter, etc. Edge-preserving filtering has many applications since it can smooth an image and at the same time preserve its structure well. It means the spatial information is considered in the filtering process. For the second assumption in [13] i.e. to ensure that the neighboring pixels on the same side of an edge have similar pixel values, transform domain recursive filtering is used. Recursive filters are an effective way of achieving a long impulse response without having to perform long convolution. They execute very rapidly. These filters are also called as IIR filters since their impulse responses are composed of decaying exponentials. In recursive filters, each point in the output signal is obtained by multiplying the values from the input signal by the ‘a’ coefficients, multiplying the previously calculated output values by the ‘b’ coefficients and adding their products together.

$$y[n] = a_0x[n] + a_1x[n-1] + a_2x[n-2] + a_3x[n-3] + \ldots.. + b_1y[n1] + b_2y[n-2] + b_3y[n-3]+\ldots \quad (3)$$

where $x[n]$ is the input signal, $y[n]$ is the output signal, a and b values are the recursion coefficients. Eq(3) is called the recursion equation and the filters that use this equation are called recursive filters. These filters are useful because they bypass a longer convolution.

D. Transform domain recursive filter

Transform domain means the input signal I is transformed to the transform domain Ω_w. For every pixel the transform coordinate $ct(x_m)$is computed such that the two pixels which lie on the same side of the strong edge have nearby coordinates whereas pixels on different sides are far apart. This transformed signal is then processed by using recursive filtering as follows:

$$J[m] = (1-a^b)\, I[m] + a^bJ[m-1] \quad (4)$$

where $J[m]$ is the filtered result, $a = exp(-\sqrt{2/\delta_s})\ \epsilon\ [0,1]$ is a feedback coefficient with δ_s as the spatial parameter, $I[m]= I[x_m]$ is the input signal and b is the distance between the neighbour samples x_m and x_{m-1} in the transform domain. b is estimated as $b= ct(x_m) - ct(x_{m-1})$. The function $ct(u)$ defines the domain transform of the signal I[x] as follows:

$$ct(u) = \int_0^u 1 + \frac{\delta_s}{\delta_r}|I'(x)|dx, \quad u\ \epsilon\ \Omega_w \quad (5)$$

where $I'(x)$ is the derivative of input signal $I(x)$ and δ_s and δ_r are the spatial and range parameters of the EPF respectively. From (4) it is seen that as b increases a^b will come closer to 0 thus stopping the propagation chain and preserving the edges. The pixels on the same side of edge will have similar filtering outputs. In the 2-D image case, 1-D filtering is first performed along each image row and then again along image column.

III. IMPLEMENTATION DETAILS

The hyperspectral data set of the Indian pines image is used. The Indian pines image is for the agricultural test site of the Northwestern Indiana. It was acquired by the AVIRIS sensor. The image has 220 bands of size 145x145, with a spatial resolution of 20m per pixel and a spectral coverage ranging from 0.4 to 2.5 µm. Twenty water absorption bands (no. 104-108, 150-163 and 220) were removed. Figure 3 gives the results of the image fusion technique. There are a total of 200 bands in the Indian pines hyperspectral image. These 200 bands are divided into 10 subsets, thus each subset having 20 bands. These 20 bands in each subset are fused together using averaging technique and the results for the 10 subsets are given in figure 3. Transform domain recursive filtering is then applied to the fused bands i.e. the 10 subsets obtained from the image fusion technique. This is shown in figure 4. These are the resulting IFRF features.

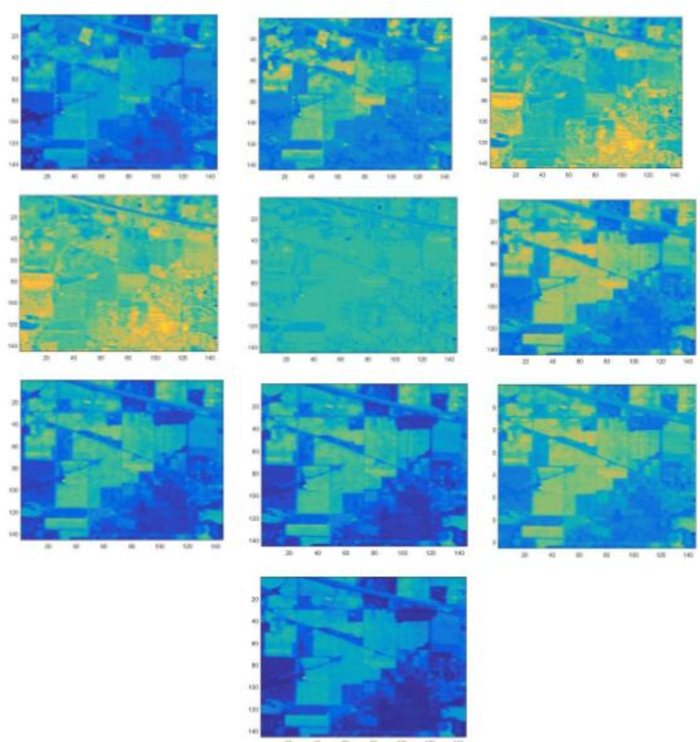

Figure 3: Image fusion outputs obtained by using averaging technique for the 10 subsets

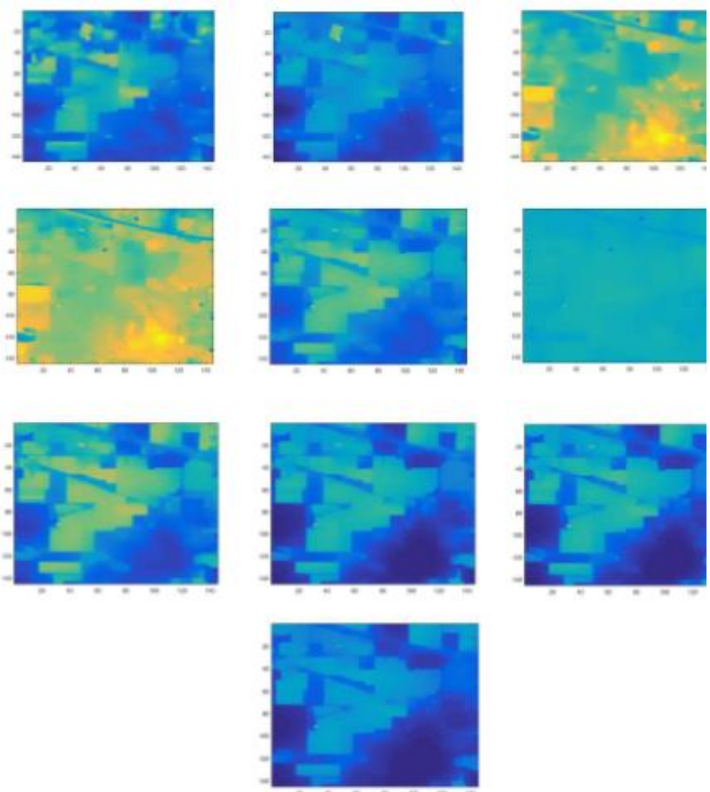

Figure 4: Filtered outputs obtained by transform domain recursive filtering of the 10 IF subsets

V. CONCLUSION

In this paper, the high dimensionality of hyperspectral images is discussed. This high dimensionality leads to a problem named Hughes phenomenon. Feature extraction is an important technique to reduce the dimensionality. So a simple approach for the feature extraction of hyperspectral images is studied and implemented. This IFRF based feature extraction method is based on the application of image fusion to reduce the dimension of the hyperspectral image along with recursive filtering to combine the spatial information. The IFRF features are thus obtained.

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