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IFRF for efficient Feature Extraction

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***Abstract*— Feature extraction is known to be an effective way in both reducing computational complexity and increasing accuracy of hyper spectral image classification. In this project, a simple yet quite powerful feature extraction method based on image fusion and recursive filtering (IFRF) is proposed. First, the hyper spectral image is partitioned into multiple subsets of adjacent hyper spectral bands. Then, the bands in each subset are fused together by averaging, which is one of the simplest image fusion methods. Finally, the fused bands are processed with transform domain recursive filtering to get the resulting features for classification. Experiments are performed on different hyper spectral images, with the support Fuzzy classifier. By using the proposed method, the accuracy of the Fuzzy classifier can be improved significantly. Furthermore, compared with other hyper spectral classification methods, the proposed IFRF method shows outstanding performance in terms of classification accuracy and computational efficiency.**

***Index Terms*— Feature Extraction, IFRF, Hyper Spectral Images**

I. Introduction

Remote sensing can be defined as collection and interpretation of information about an object, area or event without any physical contact with the object. Aircraft and satellites are the common platforms for remote sensing of earth and its natural resources. Aerial photography in visible portion of the electromagnetic wavelength was the original form of remote sensing but technological developments has enabled the acquisition of information at other wavelength including near infrared, thermal infrared and microwave.

Collection of information over a large numbers of wavelength bands is Remote sensing image acquired by multispectral sensors such as the widely used Lands at. Thematic Mapper sensor, have shown their usefulness in numerous earth observation applications. However, their discrimination capability is very limited when different types (or conditions) of the same species (e.g., different types of forest) are to be recognized. Hyperspectral sensors can be used to deal with this problem. These sensors are characterized by a very high spectral resolution that usually results in hundreds of observation channels.

Hyperspectral remote sensors collect image data simultaneously in dozens or hundreds of narrow, adjacent spectral bands. These measurements make it possible to derive a continuous spectrum for each image cell. However, developing efficient methods to process hyperspectral images with more than 100 channels is a difficult objective. From a methodological viewpoint, the automatic analysis of hyperspectral data is not a trivial task. In particular, it is made complex by many factors, such as: 1) the large spatial variability of the hyperspectral signature of each land-cover class; 2) atmospheric effects; and 3) the curse of dimensionality.

II. EXISTING SYSTEM

In [1], a new image fusion method is proposed based on the integration of wavelet and fast discrete curvelet transform, which describe the curved shapes of images and analyses feature of images better. This paper uses MRI and CT images for fusion which contains complementary information helpful for diagnosis of disease. The fusion results obtained from proposed method are analyzed and compared visually and statistically with different types of wavelets used in image fusion. The results of proposed method are efficient and improve the Entropy, PSNR, Mean, STD and MSE. The proposed method can be helpful for better medical diagnosis.

[2] focuses on the comparison of the image fusion methods which utilize the wavelets of the above three general classes. The typical wavelets from the above three general classes – Daubechies (Orthogonal), spline biorthogonal (Biorthogonal), and À trous (Nonorthogonal) – are selected as the mathematical models to implement image fusion algorithms.

Image fusion is a tool for integrating a high-resolution panchromatic image with a multispectral image, in which the resulting fused image contains both the high-resolution spatial information of the panchromatic image and the color information of the multispectral image. Wavelet transformation, originally a mathematical tool for signal processing, is now popular in the field of image fusion. Recently, many image fusion methods based on wavelet transformation have been published. The wavelets used in image fusion can be categorized into three general classes: Orthogonal, Biorthogonal and Nonorthogonal. Although these wavelets share some common properties, each wavelet leads to unique image decomposition and a reconstruction method which leads to differences among wavelet fusion methods.

When wavelet transformation alone is used for image fusion, the fusion result is often not good. However, if wavelet transform and IHS transform are integrated, better fusion results may be achieved. Because the substitution in

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IHS transform is limited to only the intensity component, integrating of the wavelet transform to improve or modify the intensity and the IHS transform to fuse the image can make the fusion process simpler and faster. This integration can also better preserve color information. The fusion method based on the above IHS and wavelet integration concept is employed in this paper. IKONOS image data are used to evaluate the three different kinds of wavelet fusion methods mentioned above. The fusion results are compared graphically, visually, and statistically.

In [3], a filtering scheme is proposed that can remove both the additive Gaussian noise and the impulse noise. Additive Gaussian noise is characterized by adding to each image pixel a value with a zero-mean Gaussian distribution. Such noise is usually introduced during image acquisition. The zero-mean distribution property allows such noise to be removed by averaging pixel values locally .Traditional linear filters can remove noise effectively but with the side effect of blurring edges and details significantly. The more advanced methods for noise removal aim at preserving edges and details in images while removing the noise. Tomasi and Manduchi propose a bilateral filter that uses weights based upon spatial and radiometric similarity. The bilateral filter has good results in removing noise while preserving edges in images. In addition, this method is non iterative, local and simple. Non iterative, local and simple.

Impulse noise is characterized by replacing a portion of an image pixels with noise values, leaving the remainder unchanged. Such noise is introduced due to acquisition or transmission errors. Nonlinear filters have been developed for removing impulse noise such as the traditional median filter. Extensions of the median filter are proposed to meet various criteria, e.g., robustness, preservation of edge, or preservation of details.

III. PROPOSED SYSTEM

The method is based on two simple assumptions: 1) the adjacent bands of the hyper spectral image usually contain redundant information, and 2) the neighboring pixels usually have quite strong correlations with each other. The adjacent bands of the hyper spectral image look quite similar. Based on this observation, IF is adopted to combine the complementary information of adjacent bands for feature reduction. One advantage of IF is that it can effectively remove noise and can preserve well the structural information of the image in the fused bands.

For the second assumption, transform domain recursive filtering is utilized to ensure that neighboring pixels on the same side of an edge have similar feature values. In other words, spatial context information is also well utilized in the feature extraction process. Experimental results demonstrate the outstanding performance of the proposed IF and recursive filtering (IFRF) based feature extraction method in terms of classification accuracy and computational efficiency. It means that the two basic assumptions, i.e., spectral redundancy and spatial consistency, are both very useful in feature extraction of hyper spectral images.

Transform domain means that the input signal I is first transformed to the transform domain $\Omega\omega$. Intuitively, the transformed coordinate $ct(xm)$ is computed for each pixel such that the two pixels which lie on the same side of a strong edge have nearby coordinates, while pixels that lie on different sides of a strong edge are far apart. The transformed signal is then processed by recursive filtering as follows: a feedback coefficient, with δs as the spatial parameter; $I[m] = I(x_m)$ is the input discrete signal; and b is the distance between neighbor samples x_m and x_m-1 in the transform domain (Ω_ω) which is estimated according to $b = c_t(x_m) - c_t(x_m-1)$. The function $c_t(u)$ which is used to compute the distance b defines the domain transform of a signal $I(x)$ as follows: From (1), it can be seen that, as b increases, ab will become close to zero, stopping the propagation chain.

Therefore, edges are preserved, while pixels on the same side of the edge will tend to have similar filtering outputs. In the 2-D image case, the 1-D filtering operation is separately performed along each dimension of the image iteratively. In other words, 1-D filtering is first performed along each image row and then along each image column. In it has been shown that three iterations of 1-D filtering are able to obtain satisfactory filtering results for an image. Therefore, three iterations of 1-D filtering are adopted for the recursive filtering used in this paper. Here, the influence of the two parameters δ_s and δ_r on the filtering results is analyzed, it can be seen that the recursive filter can effectively remove the texture information and can also preserve the strong edge structures.

As δ_r and δ_s increase, a more obvious smoothing effect will be produced on the filtering outputs. Moreover, when δ_r becomes relatively large, i.e., $\delta_r = 2$, the filtering output will tend to be extremely smooth, and only little useful information is then preserved. By contrast, when δ_s tends to approach infinity, e.g., $\delta_s = 800$, the recursive filter will not produce unbounded smoothing of the image.

The image fusion method averaging will produce false colors. The disadvantage of spatial domain approaches is that they produce spatial distortion in the fused image. In the proposed method to reduce the false colours and there by increasing the image quality Wavelet Transform is used for the image fusion. The reason has been clearly analyzed. In the influence of the two parameters on the classification performance of the proposed method will be analyzed further.

The proposed feature extraction and classification approach consists of four steps: 1) partition the hyper spectral image into multiple subsets of adjacent bands; 2) fuse the adjacent bands in each subset; 3) perform recursive filtering on the fused bands; and 4) perform classification on the filtered images. It can be seen that the feature reduction step with IF is before the recursive filtering step. The reason is that performing recursive filtering before the fusion means that each hyper spectral band should be filtered, which will be much more time-consuming.

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IV. RESULTS AND DISCUSSION

The HS band image is divided into Set of sub bands. This sub bands classified depends upon the RGB bands.

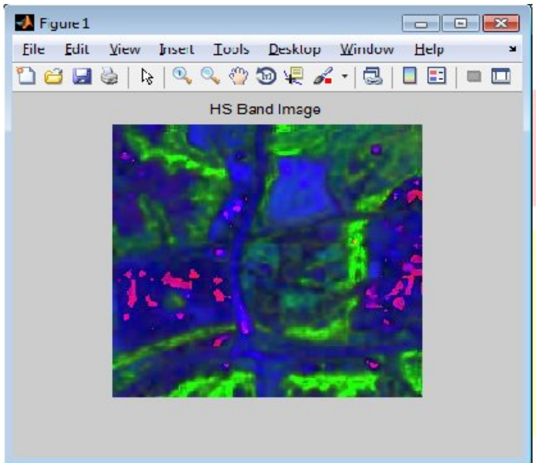

Fig.1. HS band image

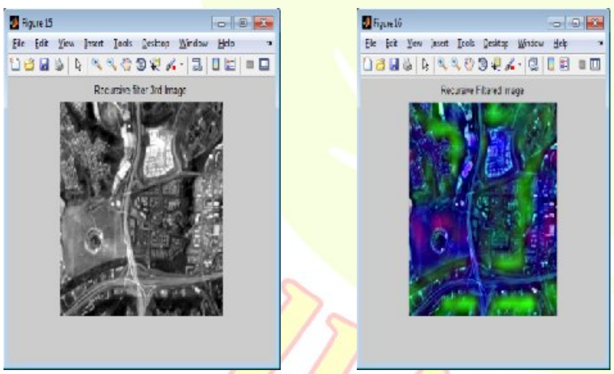

Fig.2. Recursive filtered image results

The noises removed from the fused images by using recursive filtering method.

V. CONCLUSION

Feature extraction is known to be an effective way in both reducing computational complexity and increasing accuracy of hyper spectral image classification. In this project, a simple yet quite powerful feature extraction method based on image fusion and recursive filtering (IFRF) is proposed. First, the hyper spectral image is partitioned into multiple subsets of adjacent hyper spectral bands. Then, the bands in each subset are fused together by averaging, which is one of the simplest image fusion methods. Finally, the fused bands are processed with transform domain recursive filtering to get the resulting features for classification. Experiments are performed on different hyper spectral images, with the support Fuzzy classifier. By using the proposed method, the accuracy of the Fuzzy classifier can be improved significantly. Furthermore, compared with other hyper spectral classification methods, the proposed IFRF method shows outstanding performance in terms of classification accuracy and computational efficiency.

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