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Segmentation of Multispectral Images using Local Spectral Histogram and Regression Method

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Abstract— **High resolution satellite imagery has become an significant source of information for geospatial applications. In this paper, we developed a novel method for automatically segmenting images into different regions consequent to various features of texture, intensity. Image segmentation can be performed on raw data, but also on transformed for high resolution images, on textural features. Segmentation of high resolution satellite images is useful for obtaining more well-timed and accurate information. Linear filters which used to provide improved spatial patterns and we compute combined texture and spectral features for each pixel location using local spectral histograms. Each feature as a linear combination of number of representative features and each of which corresponds to a segment. Segmentation is the method partitioning into different regions which estimating combination weights, it designate segment ownership of pixels. We also investigated the scale issue and algorithm automatic scale selection.**

***Keywords* - Texture, Spectral histogram, Scale, Segmentation.**

I. INTRODUCTION

High resolution satellite imagery has become an significant source of information for geospatial applications. As Information available from earth's observation is in high spatial and spectral resolution, an object based is an image analysis approach which receives more attention in analyzing remote sensing data [1]. Compare to traditional pixel based analysis, object based analysis uses regions of an image as a basic units, which has number of advantages, including more contextual and spatial information such as topological relationships and shape, reduced spectral variability. A major step in object based analysis is segmentation of image, which make partition of an image into nonoverlapping regions in such that each region is as homogeneous and its neighbouring different as different as possible. Actually image segmentation is the process of dividing images into spatially units and these regions represents areas in the image or discrete objects. Image segmentation is performed as a processing step for several image understanding application, example in some land cover and land use classification. Segmented images are useful in many ways also, segmented images can be easy to interpret, and by highlighting specific objects in an image. But automating the image segmentation is difficult. Image segmentation has been studied extensively. As the multispectral images, those are the mainly acquired by remote sensing radiometers, which provide more enhanced capabilities of characterizing objects of ground. While, high-resolution images contain very rich texture information, which has been shown to improve segmentation results [2][3]. Hence, segmentation methods in remote sensing are expected to make use of both texture and spectral information [4][5].

It is very difficult to characterize the visual texture. In such image analysis, morphological transformations are deal with texture information[6]. But morphological operations have limited forms and lack the ability to describe complex textures. While semivariogram can be used for texture analysis[7], but its drawback is cost is high, because of it uses number of bank of filter for extract features. In several cases, spectral information is not enough to classify them from others. Such as in urban areas, roads have related spectral characteristics with many objects, like parking lots and buildings. Hence, it is necessary to include other types of information such as texture, shape etc.

In this paper, we use local spectral histogram to capture both spectral and texture information. Here it uses Gabor filter texture analysis and Log filter for accurately localize boundries. While studying remote sensing images, segmentation is linked with scale issue. As we know that , meaningful structures and objects exist having certain range of scales. In such image analysis, scale referes to size of operators used to extract useful information form image. But Improper scaling leads to oversegmentation, means segments corresponds to portions of regions or it may lead to undersegmentation in which one segment contain multiple land cover classes. In this we are working with automatic scale issue. Using local spectral histogram representation, which consists of histograms of responses of filter in a local window. This representation provides a valuable feature to capture both texture and spectral information. But, as a form of texture descriptors, local spectral histograms also endure from the problems of boundary localization. To deal with these problems, we make use of a recently proposed method of segmentation, which formulates segmentation as linear regression. This method will works across different bands in a computationally competent way and accurately localizes the boundaries.

II. BLOCK DIAGRAM OF SYSTEM

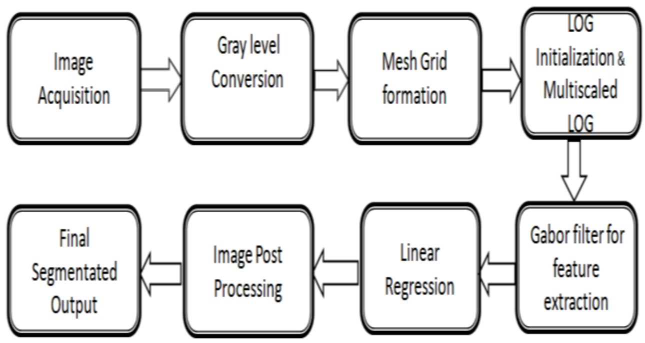

Fig. 1. Block Diagram of Proposed system.

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Given an input image with window **W** and the bank of filters *{F(α), α = 1, 2, . . . , K}*, and we can compute subband image **W**(*α*) for every filter *F*(*α*) through the convolution. For **W**(*α*), we have the resultant histogram, which denoted by *H*(*α*)w. Spectral histogram can defined as the concatenation of the all histograms of different filter responses.

$$H_w = \frac{1}{|W|}(H_{w,}^{(1)} H_{w,}^{(2)} ,\ldots\ldots\ldots\ldots, H_w^{(K)}) \qquad (1)$$

The size of the window which considered as integration scale. The spectral histogram characterizes both global patterns through a histogram and local patterns via filtering. With properly selected filters, spectral histogram is adequate to capture texture appearance. A local spectral histogram computed over a window which centered at a pixel location, is essentially a feature vector containing of local distributions of filter responses. We use an Gabor filter, which has the following form :-

$$\text{Gabor}(x,y|\sigma,\theta)= e^{-\frac{1}{2\sigma 2}[(x\cos\theta+y\sin\theta)2+(-x\cos\theta+y\sin\theta)2]} \times\cos[\frac{2\pi}{\lambda}(x\cos\theta + y\sin\theta)] \qquad (2)$$

where ,*θ* defines the orientation of the filter. Gabor filters are generally band pass filters which are used for feature extraction and texture analysis in image processing. Impulse response of filters is obtained by multiplying an Gaussian envelope function with a complex oscillation. Gabor provide the optimal resolution in both the frequency and time domains, Gabor wavelet transform seems to be the best possible basis to extract local features. In all kinds of window functions, the Gabor function is proved and performs the best analytical resolution in the joint domain. And LOG filter is given by,

$$\text{LOG}(x,y|\sigma) = (x^{2} + y^{2} - 2\sigma^{2})\, e^{\frac{-x2+y2}{2\sigma 2}} \qquad (3)$$

Where *σ* determines the scale for both types of filters. Laplacian are derivative type of filters used to find out the areas of rapid change (edges) inside the images. While these derivative filters are extremely sensitive to noise, hence it necessry to smooth the image using a Gaussian filter before applying the Laplacian. And this two step process is the Laplacian of Gaussian (LoG). There are various ways to find an discrete convolution kernal that approximates the effect of Laplacian. A smoothing Gaussian filter, combine the Gaussian and Laplacian functions to obtain a single equation as mentioned above equation(3). The LoG operator takes the second derivative of image and where the image is uniform, LoG will give zero. Also wherever a change occurs, it will give a positive response on darker side and negative response on the lighter side. At the sharp edge between two regions, the LOG will be zero away from the edge, positive just to one side, negative just to the other side and zero at point in between on the edge itself. Local spectral histograms are able of capturing both texture and spectral information for remote sensing images. We apply filters to each spectral band, the intensity filter gives spectral intensities, other linear filters generate subband images which enhance certain spatial structures. Local spectral histograms are calculated from local windows across all the bands, which define a region appearance based on spatial and spectral properties.

To extract meaningful texture features, the integration scale must be large, which makes expensive the computing of local spectral histograms. Solution to this problem, a fast implementation method based on integral histogram images. For an input image, an integral histogram image is given by : at location (*x, y*) the integral histogram is computed using the pixel values above and to the left of (*x, y*). The integral histogram at each pixel location can be calculated in one pass over the image for the reason that an integral histogram can be obtained based on that at its preceding pixel location. After computing all integral histograms in the image, the histograms of rectangular regions can obtained with four references. Fig. 1, we can obtain the histogram of region *R* using below four references as given by, L4 + L1 – L2 – L3.

Therefore, if the integral histogram image is computed, we need only three vector arithmetic operations to get any local spectral histogram whatever the window size.

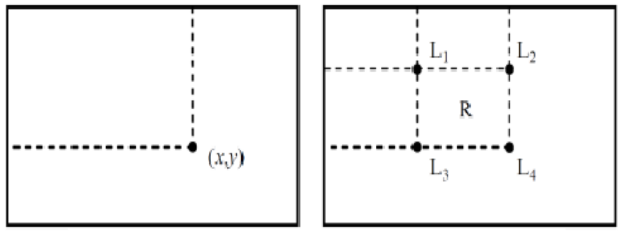

Fig. 2. Implementation of fast implementation for computing local spectral histograms. (a) The integral histogram value at location (x,y) is histogram of the image window to the left and above of (x,y). (b) Histogram of region R can be computed using four references: $L_4 + L_1 - L_2 - L_3$.

III. Segmentation Algorithm

A. Segmentation using linear regression :

Local spectal histogram is capable of to provide feature vector. Segmentation method using feature distance to measure region homogeneity. But it tends to produce inaccurate boundries caused by features extracted in image windows that cross multiple regions. Consider an image in which three different fields placed is as shown in Fig.1(a), the local spectal histogram computed at pixel location A using square window which crosses two regions, as feature does not carry discriminative data and hence this pixel is difficult to classify correctly by measuring the similarity.

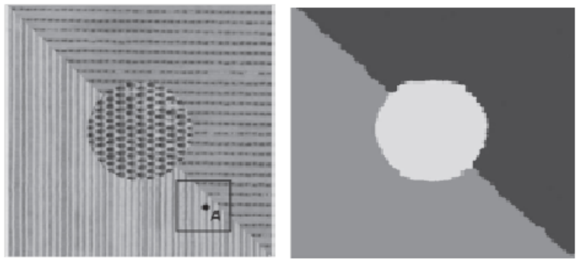

Fig. 3. Image segmentation via linear regression. (a) Texture image with. At pixel location A, local spectral histogram at location A is computed within the square window. (b) Segmentation result using linear regression. Each region is represented by a distinct gray value.

We consider that local spectral histograms within a homogeneous region are almost constant. Then we have a representative feature for every region. Consider only intensity

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filters which simplifies local spectral histograms to of pixel intensity's local histograms. The local histogram of pixel *A* is approximated by a linear combination of two histograms signifying two neighbouring regions, and the combination weights referred to the area coverage within the window. Therefore, we can assign such pixel to the region, whose histogram weight is larger. So the linear relationship between a representative features and boundary feature holds of other filter responses, apart from when the of filters scales are very large and which can significantly disfigure histograms near boundaries. While filtering in spectral histograms aims is to capture basic spatial patterns and use of large scale filters is discouraged. Although, a filter may have strong responses to region boundaries, it doesn't have a major effect on the local spectral histograms, which are computed from a larger local window. With the this analysis, each feature in an image can be considered as a linear combination of all the representative features and it is weighted by the fractional area coverage in local window.

An image with *N* pixels, and *M*-dimensional features at each pixel, whereas *L* representative features. We use linear regression model to relate each feature to the representative features and it is expressed as

$$Y = Z\beta + \varepsilon \tag{4}$$

Where Y is an $M \times N$ matrix, each every column representing a feature at a pixel location, Z is an $M \times L$ matrix contains L representative features, and the β is an $L \times N$ matrix contains combination weights for N pixels. Whereas ε is an $M \times N$ matrix represents noise. The feature matrix Y and the representative feature set Z, we seek out to estimate β that models the relationship between the representative features and feature matrix. This can be solved by the least squares estimation.

$$\hat{}\beta = (Z^T Z)^{-1} Z^T Y \tag{5}$$

The result of segmentation is given by ^β , and largest weight in every column indicates the segment ownership of the corresponding pixel.

B. Automatic scale selection :

Local spectral histograms which involve two types of scale parameters name as integration scales and filter scales both of which have an effect on segmentation results. Using proper filter scales, spatial patterns can be enhanced, which are important for characterizing region appearances and integration scales need to be large to capture meaningful features. But too large scales will be result into overly smooth segmentation . Without any prior concept, it is a challenging task to find scales which lead to optimal segmentation results. Here, we tried to this problem by studying singular values of a feature matrix as it does not require segmentation at different scale levels.

In the low-rank approximation, error of approximation where it is related to the singular values of the original matrix given by ,

$$Y - Y_r' = \sqrt{\sum_{i=r+1}^{M} \sigma_i^2} \tag{6}$$

In above equation, Y_r' is rank –r approximation error, Where σ_1 , $\sigma_2 \ldots \sigma_M$ are the singular values.

Hence, We have

$$\sigma_r^2 = \sum_{i=r}^{M} \sigma_i^2 - \sum_{i=r+1}^{M} \sigma_i^2 = \|Y - Y'_{r-1}\|^2 - \|Y - Y'_r\|^2 \tag{7}$$

Where r is current rank and r+1 is rank obtained by iteration. The increment in rank result in which reduces approximation error. The value of σ_{r+1} should be minimum as it corresponds to noise. Hence the integration is based on two values r and σ. Ratio of σ_r to σ_{r+1} gives the integration scale h and this ratio can be computed by $R_{ah.}$ The integration scale is mathematically expressed as :

$$h = \max \{(h : R_h < \omega)\} \tag{8}$$

Where means threshold. So, we choose the scales based on these two singular values. First we determine filter scales. For a proper solution, we need to select both filter scales and filter types. To make the problem more submissive, we assume that for an image, a filter bank is known to be sufficient to differentiate texture appearances, where the filter scales are the only adjustable parameters. Consequent filters in two filter banks have scales of the same proportion; thus, all filter scales in filter bank depend on the single value.

IV. Experimental Results

We have applied our algorithm to the image of size 600 × 398. Fig. 4. shows the results of segmentation for which fig 4.a) is original image on which the algorithm mentioned in section III is applied. Here, we use the filters mentioned in section II to calculate local spectral histograms. First we convert image into gray scale image and smoothened it. Then extraction of boundary features and as we can see, the regions with different textures are separated successfully, and the boundaries are localized well due to feature decomposition. The inaccuracy of the boundaries is mostly caused by similar texture appearances. Although texture appearance inside some regions varies noticeably, the segmentation results are not much affected. We attribute the robustness to both the texture features used and effective least square solutions.

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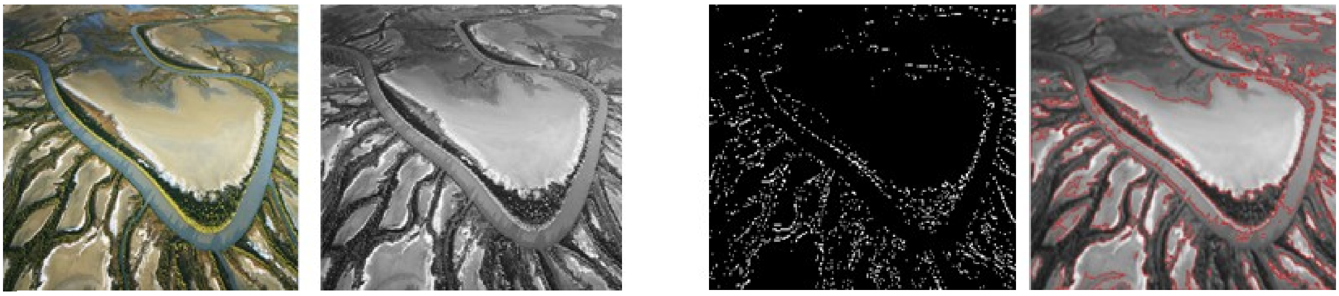

a) b) c) d)

Fig.4. Original input Image is taken is of size 600 × 398. a) Original Image , b) Gray Scale Image, c) Boundary feature extraction , d) Segmentation result using proposed method

V. CONCLUSION

We have presented a new method for remote sensing image image segmentation based on texture and spectral features. We use local spectral histograms to make available combined features. However each feature is a linear combination of representative features, we formulate the segmentation difficulty as a linear regression, which can be solved by least squares estimation. We also investigated the scale issue and an algorithm is presented for automatically select proper scales, which does not require segmentation at multiple scale levels

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