SEGMENTATION OF HIGH-RESOLUTION SATELLITE IMAGERY BASED ON FEATURE COMBINATION

S. Wang[a], A. Wang[a,]

[a]School Of Remote Sensing Information Engineering, Wuhan University, 129 Luoyu Road, Wuhan 430079, China
wangsg@whu.edu.cn, wap531@163.com

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ABSTRACT:

High resolution (H-res) satellite sensors provide rich structural or spatial information of image objects. But few researchers study the feature extraction method of H-res satellite images and its application. This paper presents a very simple yet efficient feature extraction method that considers the cross band relations of multi-spectral images. The texture feature of a region is the joint distributions of two texture labelled images that are calculated by its first two principal components (PCs) and the spectral feature is that of grayscale pixel values of its two PCs. The texture distributions operated by a rotation invariant form of local binary patterns (LBP) and spectral distributions are adaptively combined into coarse-to-fine segmentation based on integrated multiple features (SIMF). The performance of the feature extraction approach is evaluated with segmentation of H-res multi-spectral satellite imagery by the SIMF approach.

1. INTRODUCTION

High-resolution (H-res) satellite images have become commercially available and have been increasingly used in various aspects of environmental monitoring and management. The fine resolution satellite imagery makes it possible to detect the land cover/use type in detail. But on the other hand as the H-res satellite sensors increase the within field spectral heterogeneity and the traditional pixel-based image analysis method will produce many salt and pepper image areas. Object based image analysis (OBIA) method that makes it possible to get inferences based not only on spectral properties, but also on information such as object shape, texture, spatial relationship as well as human knowledge are proving to be useful in this high spatial resolution world. A necessary prerequisite for OBIA is successful image segmentation.

As the traditional pixel-based segmentation/classification methods have some limitations, especially when they are applied to H-res satellite imagery. Recently, H-res satellite image segmentation has drawing considerable attention. Several new segmentation methods have been examined by a number of authors. The fractal net evolution approach (FNEA) is embedded in the commercial software environment (Hay et al. 2003) and was thoroughly introduced by Baatz and Schäpe (2000). Various research projects have demonstrated the potential of this multi-scale segmentation approach (Hay et al. 2003), yet it still suffers from some limitations, i.e., it cannot be fully exploited because of lack of a theoretical framework and users have to find useful segmentation levels by ‘trial and error’ (Hay et al. 2003). Pesaresi and Benediktsson (2001) proposed a new morphological multiscale segmentation method based on the morphological characteristic of connected components in images, which is however only suited for complex image scenes such as city area of H-res satellite images. Examples of more recent approaches include segmentation by the floating point based rain-falling watershed algorithm and a region adjacency graph based multi-scale region merging (Chen et al. 2004; Chen et al. 2006), multiscale object-specific segmentation (MOSS) (Hay et al. 2005), segmentation based on the Gaussian Hidden Markov Random Field model (Gigandet et al. 2005) and automatic segmentation of H-res satellite imagery by integrating texture, intensity and color features (Hu et al. 2005).

There have been some research on segmentation method based on combining multiple features (Chen and Chen 2002; Hu et al. 2005). Chen and Chen (2002) evaluated a color texture segmentation approach combining color and local edge patterns by constant weights, however the method only performs well on some simple color texture images and natural scenes and it is not suitable for complex H-res satellite images. The approach presented by Hu et al. (Hu et al. 2005) performs relatively well on H-res satellite imagery but the weights of three features are hardly to determine. As in our previous research work (Wang *et al.* 2007), SIMF by the features including texture and spectral distributions that are described in the paper and colour feature which is the Hue/Saturation histogram and by the weight combination similar to (Hu et al. 2005) performs well on few images. So we will make some comparison with segmentation approach combing the texture and feature distributions.

In segmentation based on integrated multiple features (SIMF), the choices of highly discriminating features (Ojala and Pietikainen 1999) and how to combine the features are the most important factors for a successful segmentation. In this paper, we present a region-based unsupervised segmentation method, which utilizes features integrating texture and spectral distributions. The two features are then used to measure the similarity of adjacent image regions during the coarse-to-fine segmentation process (Chen and Chen 2002; Hu et al. 2005; Ojala and Pietikainen 1999). The main objective of this research is to examine the ability of the new feature extraction method in segmentation of H-res satellite images and easiness of SIMF by two features.

The paper is organized as follows. In section one some background and the objective of this research are introduced. Section two introduces the feature extraction method in this paper. The segmentation methodology is presented in section three. In section four, we carry out several experiments and demonstrate the segmentation results. Section five concludes the paper with discussion and conclusion.

2. FEATURE DESCRIPTION

In the whole segmentation process, we utilize a novel texture and spectral feature extraction method which considers the cross-band relations between pixels. Principal Component Analysis (PCA) is adopted in this study to get rid of redundant information and make it convenient to extract texture features of multispectral images. More specifically, we obtain the first two principal components (PCs) of multispectral (i.e. blue, green, red and near infrared) H-res satellite imagery through PCA. They collect most of the information of the H-res imagery. Then the texture and spectral information is calculated from the transformed PCs. The distributions of texture and spectral information are denoted by discrete two-dimensional histograms whose two dimensions correspond to the two PC variables respectively.

2.1 LBP texture operator

The texture analysis operator of LBP (Local Binary Pattern) was first introduced as a complementary measure of local image contrast by Ojala et al. (Ojala et al. 1996) and was extended by subsequent studies. Due to its major advantages on simple theory, computational simplicity and robustness to rotation and monotonic transformation of gray scale, it has been frequently used in many studies, such as texture segmentation or classification (Chen and Chen 2002; Ojala et al. 2006), moving objects detection (Heikkila and Pietikainen 2006) and segmentation of remote sensing imagery (Hu et al. 2005; Lucieer et al. 2005).

The name "Local Binary Pattern" reflects the functionality of the operator, i.e., a local neighborhood is thresholded at the gray value of the center pixel into a binary pattern (Ojala et al. 2002). The original LBP was produced by multiplying the thresholded values with weights given to the corresponding pixels, and summing up the results (Maenpaa 2003). Ojala et al. (Ojala et al. 2002) proposed gray-scale invariance LBP form $LBP_{P,R}$, which is defined as

$$LBP_{P,R} = \sum_{p=0}^{P-1} 2^p s_p \tag{1}$$

Where

$$s_p = s(g_p - g_c) = \begin{cases} 0, & g_p < g_c \\ 1, & g_p \geq g_c \end{cases} \tag{2}$$

Where P is the number of neighboring pixels on a circle of radius R, g_c corresponds to the gray value of the centre pixel of a texture unit and g_p is the gray value of its neighbourhood. In order to achieve rotation invariance, Ojala et al. (Ojala et al. 2002) presented the term of 'Uniform', whose measure corresponds to the number of spatial transitions (bitwise 0/1 changes) in the patterns. However, the 'uniform' pattern is defined in the case of regular textures i.e. Brodatz's textures, which consist of the vast majority of "uniform" patterns of all 3 × 3 patterns and it is not the case of satellite imagery through our experiment. So we present a rotation invariant LBP form $LBP_{P,R}^{ri}$ that is more suitable for describing natural scenes:

$$LBP_{P,R}^{ri} = \frac{1}{P}\sum_{i=0}^{P-1}\left\{ROR(LBP_c, i) \mid i = 0,\ 1, \cdots, P-1\right\} \tag{3}$$

Where the ROR is defined as:

$$ROR(LBP_{P,R}, i) = \begin{cases} \sum_{p=i}^{P-1} 2^{p-i} s_p + \sum_{p=0}^{i-1} 2^{P-i+p} s_p, & i > 0 \\ LBP_{P,R}\ , & i = 0 \end{cases} \tag{4}$$

2.2 Texture and spectral distribution

The texture feature is extracted on gray level images in the most of the previous studies. For multi-spectral imagery, it does not consider cross-band relations (Hu et al. 2005). Although Lucieer et al. (Lucieer et al. 2005) considered the cross-band relations by multivariate texture model, the method is too complicated. In this paper, the texture feature of an image region is evaluated by the joint distribution, i.e. a discrete two-dimensional histogram, of LBP operator operated on two PCs of the image region. In the following experiments, we apply $LBP_{8,1}^{ri}$ to calculate the texture distribution LBP_1 / LBP_2 of an image region and compare their efficiency in colour image segmentation. The spectral feature of an image region is just the joint distribution of grayscale values of its two PCs. As the number of bins used in the quantization of the feature space is a trade-off between the discriminative power and the stability of the feature transform, we set the bins of spectral distribution as 32 by 32 in the following study.

2.3 Similarity measure

In the split and merge segmentation process, we choose a non-parametric statistic the G-statistic as a pseudo-metric for comparing the similarity between texture and spectral distributions. The similarity between a sample and model histograms is computed by the formula:

By our experiments, In the split and merge segmentation process, we choose a non-parametric statistic the G-statistic as a pseudo-metric for comparing the similarity between two histograms and the similarity between two regions *i* and *j* is measured by weighted sum G-statistic $WG(i, j)$ of the similarity measures of three features. Then the similarity between two regions *i* and *j* is measured by weighted sum G-statistic $WG(i, j)$ of the similarity measures of spectral and texture distributions G_s and G_t.

$$WG(i, j) = w_t G_t + w_s G_s \tag{5}$$

The weights of texture and spectral distributions w_t and w_s should be adaptively determined in terms of different characteristics of pairs of regions. If two regions are smooth, the weight of spectral distribution should tend to be large. If two regions have obvious texture characteristic, the weight of texture should be larger than that of spectra. Standard deviation (SD) can evaluate the smoothness of a region to a certain extent. Smooth region produces small SD and rough region produces large one. So we apply SD of regions to evaluate the feature weights between two regions *i* and *j*, if the SD values of two neighboring regions are less than 40,

$$\begin{aligned} u_s &= \max(SD_i, SD_j) \\ u_t &= \min(SD_i, SD_j) \end{aligned} \tag{6}$$

Or else, u_t is set to be the larger one. Where u_t and u_s are the weight estimation of the texture and spectral distributions; SD_i and SD_j are the SD of regions *i* and *j*. After normalizing the weights, we have the final result:

$$\begin{aligned} w_t &= u_t /(u_t + u_s) \\ w_s &= u_s /(u_t + u_s) \end{aligned} \tag{7}$$

By our experiment, a better way of calculating $WG(i, j)$ in the split process is by normalizing the six G-statistics. The normalized G-statistics are calculated by:

$$G_r^n = G_r / \sum_{r=1}^{6} G_r \tag{8}$$

and the weighted sum similarity between two regions $WG(i, j)$ is defined as:

$$WG(i, j) = w_s \cdot G_s^n + w_t \cdot G_t^n \tag{9}$$

3. SEGMENTATION METHODOLOGY

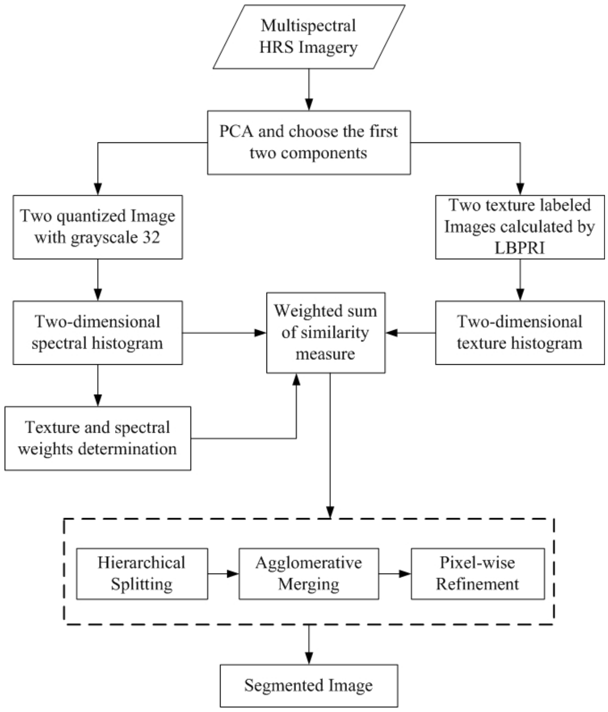

Figure 1. Region-based unsupervised segmentation adaptively combining texture and spectral distributions.

The whole segmentation framework in this paper includes three steps: hierarchical splitting, modified agglomerative merging and pixel-wise refinement (see Figure 1). Hierarchical splitting recursively split the original image into four square sub blocks of varying size based on a homogeneity test:

$$R = \frac{WG_{\max}}{WG_{\min}} > X \quad . \tag{10}$$

Where $WG_{\max}$ and $WG_{\min}$ represent the largest and smallest homogeneities among the six pairwise homogeneities of the four sub blocks. The initial divided window size is set to 64 and the smallest size is 16. The block recursively split into four sub blocks when R is greater than a threshold X. The value of X is invariant for different kind of images: X is experimentally set to 1.3 to 1.5 for regular texture images and 1.2 for H-res satellite imagery.

Once the image has been split into blocks of roughly uniform features, the blocks are merged through a modified merging procedure. At a particular stage of merging, we merge that pair of adjacent regions which has the smallest merger importance (MI) value. MI is defined as:

$$MI = \sqrt{p} \times WG \quad , \tag{11}$$

where p is the number of pixels in the smaller of the two regions and *WG* is the weighted sum similarity measure between the two regions. The reason we adopt equation (12) instead of $MI = p \times WG$ (Ojala and Pietikainen 1999) is that the latter one overrates the size of regions and makes the segmentation results unstable. In the merging process, we utilize RAG (Region Adjacency Graph) to describe the blocks after splitting. The RAG consists of three components: V, E and M. V is a set of region nodes to record the region information. E is an adjacency matrix to record the pseudo-address of each region edge. The M matrix records the merger importance values of all the pairs of adjacent regions of an image. At each merging step, we search the smallest MI of the M matrix and merge the pair of adjacent regions that has the smallest MI. Then we adjust the RAG, and merge the pair of adjacent regions that has the smallest MI in the changed M matrix. Merging proceeds until the following stopping criteria is true:

$$MIR = \frac{MI_{cur}}{MI_{\max}} > Y \quad . \tag{12}$$

Where MI_{cur} and $MI_{\max}$ denote the merger importance for the current best merge and the largest merger importance of all preceding mergers. Threshold Y is determined experimentally.

A boundary refinement algorithm is used to refine the boundaries of the blocky segmented image. For an examined boundary point P, a discrete square with a dimension d around the pixel is placed and the MI between the square and the neighboring regions of point P is computed. The pixel is relabelled if the label of the neighboring region that has the smallest MI is different from the label of P. At the following step, we only consider the boundary points that have relabelled at the previous sweep. The procedure is iterative and proceeds until the un-relabelled number of the boundary pixels is less than 50 or the iteration times are larger than 30.

4. EXPERIMENTS AND RESULTS

The objective of the present experiments was to evaluate the effectiveness of the novel features of texture and spectral distributions and the very simple weight combination approach in segmentation of H-res remote sensing imagery. Besides, we discuss the effect of several parameters, i.e. weight determination, MI and thresholds, on the result of segmentation for the purpose of obtaining improved results and finding a way of solving SIMF better.

The performance of the method was evaluated with 256×256 pixel multi-spectral IKONOS-2 satellite images. IKONOS-2 data contain red, green, blue and near-infrared (NIR) channels at 4.0 m spatial resolution. Since the colour images are the most common in application and can provide more information than grayscale images, the paper is endeavour to explore segmentation approach that make good use of multi-spectral or colour information.

The experiments were performed using the following procedure. The original multi-spectral images are transformed by PCA. We just take the first two PCs for feature extraction. They collect more than 95% information of the original images. For texture features, we computed texture labelled images of the PCs by rotation invariant LBP form and we got two LBP labelled images which were used to obtain the discrete two-dimensional texture histograms. The texture similarity of two regions was calculated by their two-dimensional texture histograms. The spectral histogram was gotten by their joint distribution of the gray-scale pixel values of the PCs. So we got the spectral similarity of two regions from their spectral histograms. The first PC was used to calculate the attribute of regions by their standard deviation, which was applied to weight determination of the two features. The weighted sum similarity measures were used to the whole coarse to fine segmentation process.

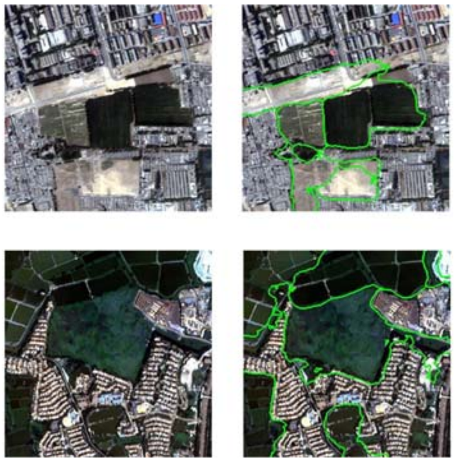

Figure 2. Segmentation results of H-res images based on texture distributions calculated by $LBP_{8,1}^{ri}$ and spectral distributions.

Figure 2 shows the segmentation results by SIMF approach based on texture distributions calculated by $LBP_{8,1}^{ri}$ and spectral distributions. The result demonstrates that the SIMF approach by our feature extraction method performs well on complex H-res satellite images.

5. DISCUSSION AND CONCLUSION

The paper presented a novel feature extraction method that considers the cross band relations and a new segmentation framework SIMF suitable for segmenting multi-spectral images. Figure 2 demonstrates the satisfied segmentation results. It shows that $LBP_{8,1}^{ri}$ is a robust LBP operator for texture feature extraction. Despite that, the feature weight determination is still a necessary research topic in the future since the images are very complex and different textures may be used to SIMF.

Based on the previous experiments and results, we point out the future research works. The feature extraction method is very important for SIMF. The future research should concentrate on finding more appropriate features adaptive to different kinds of images, e.g. that of various resolution. The feature weight combination approach determines whether the combining features can discriminate heterogeneous regions to a large extent, which is still an open problem. The MI determines the sequence of merging of pairs of homogeneous regions and the stopping criterion for merging. MIR determines when to stop the merging process and the scale of segmentation results. So the future research should explore MIR that can implement multiscale segmentation. Similarity measure of feature distributions is not as important as the previous discussed parameters. Several measures can be used, e.g. histogram intersection, Log-likelihood statistic or G-statistic and chi-square statistic.

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