ACCURACY ENHANCEMENT OF OBJECT BASED IMAGE CLASSIFICATION USING RELAXATION LABELING PROCESS FOR HIGH RESOLUTION SATELLITE IMAGES

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ABSTRACT

Image classification is an important task for many aspects of global change studies and environmental applications. In this study we compare two different classification approaches, which are Object based and Pixel based. Object Based Classification (OBC) methods are increasingly used for classification of land cover/land use from high resolution images, and often the final result is close to the way a human analyst would interpret the image. A number of properties of the regions were computed in OBC like spectral mean vector, average texture, departure from circularity, length-to-breadth ratio, area, perimeter and compactness. Image is then classified on the basis of the regions instead of the pixels. The fine spatial resolution implies that each object is an aggregation of a number of pixels in close spatial proximity, and accurate classification requires that this aspect be considered. In this paper Relaxation Labeling Processes (RLP) is explored as a post-classification refinement tool. RLP requires initial label probability values to start the refinement process which are generated using Cloud Basis Function based Neural Network (CBFNN) classifier. The nodes in the CBFNN output layer are normalized and treated as initial label probability values along with a thematic image. These label probabilities are updated by RLP on an iterative basis. Each time a small neighborhood around each pixel is employed for probability updating, and the iterative process effectively allows propagation of global information through expanding neighborhood.

KEYWORDS: Relaxation Labeling Process, Object Based Image Classification, Cloud Basis Function based Neural Network, High Resolution Satellite Images

INTRODUCTION

The remote sensing community is primarily interested in image classification of air- and space-borne imagery for land cover/land use mapping. Image classification information is used for several environmental and socioeconomic applications as well as to bring the satellite imagery to usable geographic products (Lu and Weng 2007, Wilkinson 2005). Satellite images, especially those captured by space-born sensors, have been the most important data source for urban change study in the past decade. However, classifying satellite images still remains a challenge that depends on many factors such as complexity of landscape in a study area, selected remote sensing data, and image processing and classification approaches etc. Reliable quantitative assessment based on remote sensing data depends on high quality image classification. Most of the time, land cover maps derived from remote sensing are often judged to be insufficient in quality and thus not trusted for quantitative environmental application purpose. Wilkinson (2005) based on a review of 15 years of peer-reviewed experiments on satellite image classification, observed that, there has been no demonstrable improvement in classification performance over the 15 years period though a considerable inventiveness occurred in establishing and testing new classification methods during the period. Jensen (2005) opined that there is no surprise of low reliability of remote sensing classification as 95 % of the scientists attempt to accomplish classification only using one variable i.e. spectral characteristic (color) or black and white tone.

Conventional pixel-based methods only utilizing spectral information for classification, such as parallelepiped, minimum distance from means, and maximum likelihood, are inadequate for classifying high-resolution multispectral images in urban environments (Thomas et al. 2003, Chen et al. 2004). Hence object-based approach is considered in this study and it has been quite successful for land-use and land-cover classification (Laliberte et al. 2004, Frohn et al. 2005). Object-based image classification is quickly gaining acceptance among remote sensing users and has recently begun being applied to the measurement of land cover (Laliberte et al. 2004). An image classification solution involves three main steps, pre-processing, feature extraction and classification (Duda et al. 2001). Based on this architecture, many image classification systems have been proposed, each one distinguished from others by the method used to compute the region signature and/or the decision method used in the classification step. In object-based image classification, spatial information such as texture, shape, and context can be used both to increase the discrimination between spectrally similar urban land cover types (Goetz *et al.* 2003), and to define objects composed of pixels with heterogeneous reflectance. Rather than classify individual pixels into discrete cover types, object based classification first segments imagery into small objects, which then serve as building blocks for subsequent classification of larger entities. Object characteristics such as shape, spatial relations (e.g. connectivity, contiguity, distances, and direction) and reflectance statistics, as well as spectral response, can be used in the rule base for classification. In this way, objects with heterogeneous reflectance values, such as a tree canopy, can still be recognized despite their heterogeneity.

This paper deals with use of new basis functions, called Cloud Basis Function (CBF) (De Silva *et al.* 2008) with a few modifications. It uses a different feature weighting, derived to emphasize features relevant to class discrimination, for improving classification accuracy. Support Vector Machines (SVM) and Radial Basis Function (RBF) Neural Networks are also implemented for accuracy comparison. The CBF NN has demonstrated superior performance compared to other activation functions and it gives approximately 3 to 4% more accuracy (Rizvi and Buddhiraju 2010). In this classified image, there might be an object that is incorrectly classified because of noise, ambiguity, presence of same gray value at unexpected location etc. Corrective measures require a post classification technique to get a reliable thematic image and improved classification accuracy. Relaxation Labeling Process (RLP) is one such technique that reclassifies object values using neighborhood information. Its approach is probabilistic in nature whilst updating label probabilities for an object.

The motivation behind choosing high resolution satellite imagery is that it offers a possibility for feature extraction and spatial modeling. Recent research has highlighted the importance of incorporating spatial information in the classification of very high resolution imagery (Chen et al. 2004). In low resolution satellite images, the data processing is only on a per-pixel spectral information basis. The spatial details of the objects are not captured adequately at low resolution. The high spatial and radiometric resolution of recent sensors have increased the spatial variability within objects in contrast to the integration effect of earlier sensors therefore decreases the classification accuracy of traditional per-pixel methods (Im et al. 2008). In this context, segmentation algorithms are recognized as complementary to pixel based approaches, in which it is similar to the way human interpreters work with regions instead of single pixels for supervised classification purposes. The paper has four sections. In Section 2, methodology for object-based image segmentation and classification are elaborated. Section 3 presents the experimental results and discussion. Section 4 summarizes the research findings and points out avenues for possible future works.

METHODOLOGY USED

There various steps involved in proposed methodology such as pre-processing, image segmentation, connected component labelling, feature extraction, image classification and post processing which are shown in Figure1 are common in many object-based image classification systems.

Pre-processing

Most of the satellite image analysis tasks require smoothing as a pre-processing operation to reduce image noise. Noise is a function of time and to reduce it smoothing is required in the temporal domain. However, because often only one image is available, smoothing is performed in the spatial domain. Several recent works on image smoothing explore statistical approaches for an automatic selection of parameters used in image-smoothing methods, the details of which can be seen in (Mrazek 2001) (Witkin 1983) (Rissanen 1989) (Perona et al. 1994). This paper is an attempt to adapt and extend the image smoothing strategy because the advantage of the adaptive gaussian smoothing method is that it is fully automatic, no manually selected parameters are required. A natural extension of gaussian smoothing is an adoption of the Gaussian kernel shape to the image structure. In order to

reduce over-segmentation and local variability between pixels due to high spatial and radiometric resolution, the input images are smoothed by adaptive gaussian filter before segmentation.
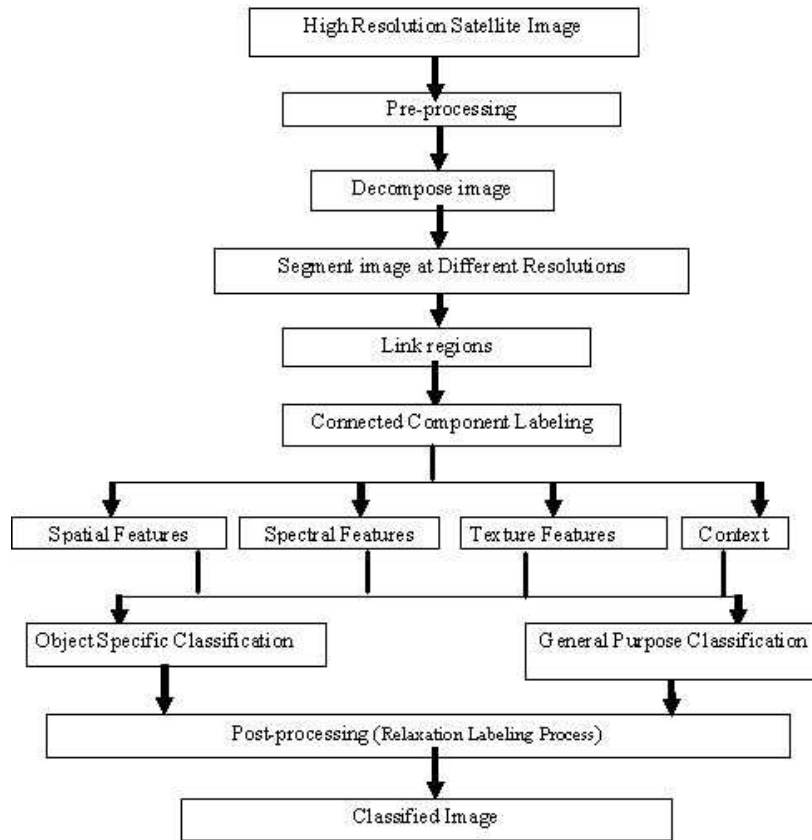

Figure 1. Proposed methodology for object based image classification using relaxation labeling process.

Image Segmentation

Any image analysis task requires a segmentation step to distinguish the significant components of the image, i.e., the foreground, from the background. Object-based analysis subdivides the image into meaningful homogeneous regions based not only on spectral properties but also on shape, texture, size, and other topological features, and organizes them hierarchically as image objects (also referred to as image segments) (Blaschke 2005). Over the last decade the analysis of Earth observation data has evolved from what were predominantly per-pixel multispectral-based approaches, to the development and application of multiscale object-based methods. In the present study, region based segmentation using morphological watershed transformation is used. The watershed transformation requires that the input image is transformed into an image where certain subsets identify elementary regions (markers) characterized by pixels with highly homogeneous grey-values. Marker based watershed transform of (Buddhiraju and Rizvi 2010) is used in this work. These markers are the regional minima found in the gradient image (Meyer and Beucher 1990), which represent a replica of the input image enhancing the edges in the zones with higher variations of grey value. Starting from the markers, an iterated growing process is activated. This can be accomplished by referring to the topographic representation of gradient image, where grey-values represent heights; in particular, valley bottoms are regional minima and correspond to markers (Haralick et al. 1987).

Connected Component Labelling and Region Parameters

Connected component labelling is a process where pixels in each non-overlapping region are given independent identity (label) so that the region parameters can be computed. An algorithm proposed by Shapiro and Stockman was used for the present study (Shapiro and Stockman 2001). Once each region is uniquely labelled, then the region shape, size, average grey level / spectral / textural properties can be computed for each region. After labelling following parameters were computed for each region. 1) Size; 2) Spatial Moments; 3) Roundness, Convexity, and Solidity 4) Mean vector; 5) NDVI 6) Texture statistics (entropy, contrast, angular second moment, etc.), 7) Length/Width ratio, 8) Area etc. (Costa and Cesar 2009). In addition to the textural and contextual measures employed, image objects also possesses shape characteristics and neighbourhood relationships (Rizvi and Buddhiraju 2010).

Object-Based Image Classification

Image classification is the process of converting the volume of digital image data into an information product. Figure 1 also shows general purpose classification which means object-based supervised classification. The rationale for selecting this approach is, it can reduce the spectral variations during image segmentation, and at the same time apply geometrical features to different objects. It does not operate directly on individual pixels but on collection of pixels (known as region or object) consisting of many spatially adjacent pixels that have been grouped together in a meaningful way by image segmentation. By adding specific features of an object, one can make general purpose classification as object specific classification technique. Many classifiers are available for classification of multi-spectral satellite images, which includes discriminate analysis, maximum likelihood classification scheme, etc. A major disadvantage of these classifiers is that they are not distribution free. This has prompted a significant increase in use of Artificial Neural Network (ANN) for classification of remotely sensed images (Mather 2004). Several other reasons can be sited in favour of Neural Network (NN) based classifiers as listed in (Han *et al.* 2002). A lot of research has been undertaken and is being carried out for developing an accurate classifier for object extraction with varying success rates. Most of the commonly used classifiers use radial basis functions (RBF) based neural networks or support vector machines for defining the boundaries of the classes. The drawback of such classifiers is that the boundaries of the classes as taken according to radial basis function networks are spherical while the same is not true for majority of the real data. The boundaries of the classes vary in shape, thus leading to misclassification. CBF algorithm is well defined in (De Silva et al., 2008).

Post-processing Technique

Initial probability for each object is generated by CBFNN, which is used as one of the input to RLP. It is an iterative process employed to reduce local ambiguities in a classified image. It does so by incorporating contextual information (neighborhood information) represented by the arrangement of labels and label compatibility constraints. Conventional RLP was originally proposed by Rosenfeld et al. (1976), which takes into account two parameters 'compatibility coefficients' and 'neighborhood support'. These two parameters represent the contextual information that plays a competent role in updating label probabilities of a pixel. Compatibility coefficients denoted by $r_{ij}(\lambda, \lambda')$, stands for compatibility of label λ at pixel i to co-occur with label λ' at neighboring pixel j. These coefficients range between [-1, 1]. Neighborhood support denotes the compatibility of a label at pixel i with the labels at neighboring pixels. Equations (1) & (2) are used for computing neighbor support and Equation (3) is used for updating label probability.

$$q_{ij}^{(k)}(\lambda) = \sum_{\lambda'} r_{ij}(\lambda, \lambda') p_j^{(k)}(\lambda') \tag{1}$$

$$q_i'(\lambda) = \frac{\sum_j q_{ij}(\lambda)}{|N(i)|} \tag{2}$$

$$p_i^{k+1}(\lambda) = \frac{p_i^k(\lambda)[1 + q_i(\lambda)]}{\sum_{\lambda} p_i^k(\lambda')[1 + q_i(\lambda')]} \tag{3}$$

Where $p_i^k(\lambda)$ denotes the probability of pixel i to belong to class λ in the kth iteration, $q_{ij}(\lambda)$ denotes the support that a pixel i receives from neighbor j, $q_i'(\lambda)$ denotes the total neighbor support and $|N(i)|$ is the cardinality of the set of neighbors of i. In equation (1) $r_{ij}(\lambda, \lambda')$ denotes compatibility coefficient. RLP technique examines probability of every defined label (i.e. different land cover/land use features) at a given pixel location. A label with higher

probability is assigned to that pixel location. A label supported strongly by the neighbors (i.e. higher value of co-occurrence) will have a higher probability following iteration. Probabilities of those labels which are opposed by the neighbors become weaker in course of the iterations. The labeling of pixels is iteratively updated such that the label assigned to a pixel is consistent with the labels present in the neighborhood. Label consistency is achieved by updating the probabilities of different labels at pixel i using the label interactions at neighboring pixels. After a number of iterations at each pixel i some label $\lambda_i (1 \le \lambda_i \le L)$, where L is total number of classes/labels, will have its probability approaching unity and the remaining ones tending to zero. The iterations continue until there is no further change in the label probabilities of pixel i for all labels, and the label that possesses the highest probability, is assigned to the pixel i.

RESULTS AND DISCUSSION

For compare of the accuracies of object-based classifier using RBFNN and CBFNN can be seen in (Rizvi and Buddhiraju 2010). Here we show our result of pixel based CBFNN and CBFNN when refined with RLP, for which we used a QuickBird window (2000 x 2000 pixels) of an urban fringe area comprising a few buildings, a quarry site, ponds, road, vegetation and foot paths. This study area on ground, it covers the Powai Area of Mumbai City as shown in Figure 2.

Figure 2. High resolution satellite image used as Study Area.

The image was classified into 9 prominent classes covering a majority of the land cover features, Lake, Pool, Vegetation, Field, Road, Shadow, Bright Roof, and Dark Roof and Mountain. Figure 3 and Figure 4 shows the output of pixel based CBFNN and post-processed CBFNN i.e. after using RLP technique respectively.
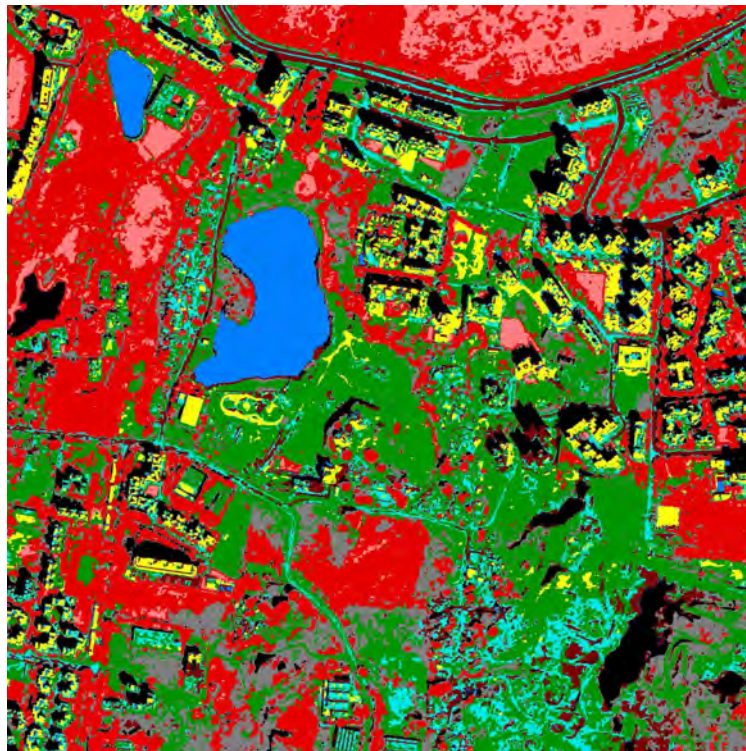
Figure 3. Classified image using CBFNN.

Figure 4. Classified image using (CBFNN+ RLP).

The success of image classification approaches is very much dependent on the quality of the image segmentation. In Figure 3 and Figure 4 misclassification between build class and road similarly between shadow class and waterbodies are very obvious because of spectral information are unable to differentiate between these classes with a high degree of accuracy. The individual class accuracies as well as overall classification accuracy for CBFNN and CBFNN with RLP is shown in Table 2. It is to be noted that overall classification accuracy increased by 1.92 per cent if RLP is used along with CBFNN. The overall accuracy is calculated by dividing the number of correctly classified pixels by the total number of reference pixels. Though simple, the overall accuracy has been the most conventional approach accuracy assessment (Woodcock 2002).

Table 1. Classification Accuracies for (CBFNN+RLP)

Classes	% Accuracy	
	CBFNN	CBFNN+RLP
Vegetation1	100	100
Vegetation2	90.13	90.49
Water	85.18	85.18
Shadows	96.29	94.44
Buildings1	91.67	91.67
Buildings2	100	100
Open Area1	91.14	95.31
Road	84.84	84.84
Open Area2	98.23	97.58
% of Overall Accuracy	**90.13**	**92. 05**

CONCLUSION

In the present work CBFNN has been used along with RLP in image classification of high resolution satellite images. The usability of such a pixel-based spectral classifier is severely limited in the arid regions mainly due to the common presence of land-covers of bare ground and dry riverbed, which have similar spectral response with built-up areas. This method is more suitable and will be the trend for the high resolution remotely sensed data. As a future watch, this classifier is to be tested with a wide variety of data and the accuracies obtained to be studied to declare it a suitable classifier for hyper-spectral images, which are going to be used in a huge range of applications, ranging from agricultural and academic purposes to military purposes. Though the CBF, being a relatively new technique in the remote sensing arena requires further study.

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