A MULTI-RESOLUTION ANALYSIS AND CLASSIFICATION FRAMEWORK FOR IMPROVING LAND USE/COVER MAPPING FROM EARTH OBSERVATION DATA

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ABSTRACT:

The last few years have seen satellite platforms with a large number of sensors (e.g. Terra and ENVISAT) coming on-line and the launching of a huge number of satellites with more than one sensor (e.g. IKONOS and QuickBird). Various satellite images with spatial resolutions ranging from 0.5 to 25,000 m are available for different applications. This development offers new and significant changes and challenges in the approach to analysis, integration, and the efficient spatial modelling of these observation data. This paper presents a multi-resolution analysis and classification framework for selecting and integrating suitable information from different spatial resolutions and analytical techniques into classification routines. The proposed framework focuses on the examination of image structural using different spatial analytical techniques in order to select appropriate methods in different stages of classification such as training strategy, feature extraction, scene models, and classification accuracy assessment. The multi-resolution approaches are tested using simulated multi-resolution images from IKNOS data for a portion of western part of the Kingston Metropolitan area. It was demonstrated that the multi-resolution classification approaches can significantly improve land use/cover classification accuracy when compared with those from single-resolution approaches.

1. INTRODUCTION

Earth observation data at multiple resolutions have been widely used in studies of environmental changes, natural resource management, and ecosystem and landscape analysis in general. With the development of new remote sensing system, very-high spatial resolution images provide a set of continuous samples of the earth surface from local, to regional scales. The spatial resolution of various satellite sensors ranges from 0.5 to 25,000 m now. Furthermore, high resolution airborne data acquisition technology has developed rapidly in recent years. As an increasing number of high resolution data sets become available such as Digital Globe (Quickbird), Space Imaging (IKONOS), Orbimage, Indian Remote Sensing (IRS), Digital Orthophoto Quarter Quads (DOQQ), etc., there is an increasing need for more efficient approaches to store, process, and analyze these data sets. The development of efficient analysis methods of using these multiscale data to improve land use/cover mapping and linking thematic maps generated from high resolution to coarse resolution has become a challenge (Foody, 2002).

The effects of spatial resolution on the accuracy of mapping land use/cover types have received increasing attention as a large number of multi-scale earth observation data become available (Dungan, 2001). Scale variation and sensitivity have played an increasingly important role in the employment of earth observation data in different application areas (Marceau et al, 1994; Atkinson and Curran, 1999; Chen et al., 2003). For example, the resolution range to identify an individual tree is much smaller than that to identify a large commercial building block. Spatial autocorrelation existing in each class is an important factor influencing classification results at each resolution level (Chen and Stow, 2003). Although many methods of semi-automated image classification of remotely sensed data have been established for improving the accuracy of land use/cover classification during the past forty years, most of them were employed in single-resolution image classification. Due to the more heterogeneous spectral-radiometric characteristics within land use/cover units portrayed in high resolution images, many applications of traditional single resolution classification approaches have not led to satisfactory results (Barnsley and Bar, 1996; Chen et al., 2003).

Several techniques have been employed to assess appropriate (or optimal) spatial resolutions. Although a particular classification can achieve the best result from a single resolution appropriate to the class, there is no single resolution which would give the best results from all classes (Marcean et al., 1994). Clearly landscapes are characterized by multiple scales of spatial heterogeneity. Landscape objects (e.g. land cover/use polygons) are not the same size and vary in different structures. Some objects are better classified at finer resolutions while others require coarser resolutions. Therefore, as suggested by Woodcock and Strahler (1987), various objects require different analysis scales according to the image scene model. Scene models may be either high (H) resolution with pixels smaller than objects, or low (L) resolution with pixels larger than objects to be mapped. From a practical standpoint, building a framework to represent, analyze and classify images represented by multiple resolutions is necessary in order to capture unique information about mapped classes that vary as a function of scale.

Many previous studies show the importance of developing and evaluating spatial analytic methods and models to support multiscale databases (Emerson et al. 1999, Li et al. 2000). The application of multiscale or multi-level approaches to earth observation data research, however, is very recent and remains limited and undeveloped. Several researchers (such as Solberg et al., 1996; Li et al., 2000) have devoted considerable effort to the development of methods to integrate and analyze multi-sensor, multi-scale and multi-temporal satellite imagery. However, compared with rapidly expanding data sets, there is an obvious lag in the development of spatial analytic methods and models for handling the increased multi-resolution images (Quattrochi and Goodchild, 1997; Tate and Atkinson, 2001).

The objective of this paper is to develop and test a multi-resolution classification framework for selecting and integrating information from different spatial resolutions to improve land use/cover classification. The multi-resolution framework is based on the development of analytical techniques and strategies of selecting and integrating suitable information from different resolutions into classification routines. The following illustrates the multi-resolution classification framework.

2. MULTI-RESOLUTION IMAGE ANALYSIS AND CLASSIFICATION FRAMEWORK

A typical computer-assisted classification involves six major steps: classification scheme design, feature transformation, training, application of classification decision rules, post-processing, and accuracy assessment. Spatial autocorrelation influences many aspects of image classification, depending on sensor resolution and landscape fragmentation. The entire classification process, especially the selection of training data, appropriate resolutions, classification algorithm, and sampling data for accuracy assessment, may be affected by the autocorrelation of neighboring pixels. A proposed multi-resolution image analysis and classification framework is based on the framework developed in Chen and Stow. (2003) and presented in Figure 1.

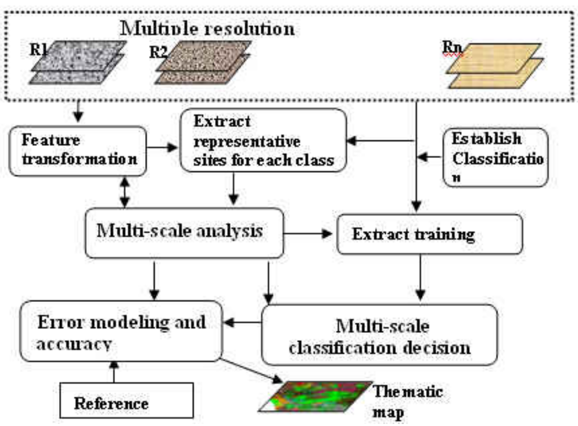

Figure 1. A proposed multi-resolution analysis framework. Rn stands for variable image spatial resolution.

The framework proposed here, focuses on the examination of image pattern, structural, and autocorrelation using different multi-scale spatial analytical techniques in order to select appropriate methods in different stages of classification such as training strategy, feature extraction, scene models, and classification accuracy. Spatial analysis techniques for measuring the pattern size and degree of autocorrelation are computed for each training class in order to determine whether they can guide selection of training data, high-resolution or low-resolution classification models, the range of spatial resolutions used for classification, and error patterns. The following sections describe the major parts of Figure 1.

2.1 Image resolution pyramids

Multi-resolution images can be created in two ways: (1) by integrating different resolution images acquired by different sensors; and (2) aggregating fine resolution images into different coarse resolution levels (i.e., image pyramids). Obtaining images of different resolutions from different sensors could have advantage of including more spectral information that can be used to identify different objects, but is expensive. The misregistration between different images also would increase the processing cost and reduce classification accuracy.

It is more efficient to extract spatial information over a range of resolutions from a single high resolution image or degradation. There are several types of methods used in the operation of aggregation including simple aggregation methods (e.g. averaging, central-pixel, median, sub-sampling, nearest neighbor, cubic convolution, etc.), scale-space transform (Lindeberg 1994), and Wavelet decomposition (Mallat 1989).

2.2 Multi-scale analysis

The purpose of multi-scale analysis is to establish a statistical model describing relationships between variables measured at different resolutions. The proper application of image classification procedures requires knowledge of the variables of the data to determine the appropriate classification methodology and parameters to use. The concept of spatial autocorrelation has been introduced as a basis for understanding the effect of scale. Spatial autocorrelation is an important factor in selecting 1) appropriate training methods for different homogenous/heterogeneous classes (Chen and Stow, 2002), 2) appropriate spatial resolutions and image scene models (L- or H-resolution), 3) suitable classification methods and parameters; and 4) understanding classification errors at the different spatial resolutions (Foody 2002).

Prior to performing image classification, exploratory spectral-radiometric data analysis and visual assessment of the spatial characteristics of each image band is recommended. Exploratory spatial data analysis should be employed to determine required information on image spatial characteristics and to ensure that appropriate scene methods and classification parameters are used.

Many spatial statistical measures have been used to establish the spatial characteristics and scene model characteristics of images and to assess the scale of spatial variation in remotely sensed data (such as local variance (Woodcock and Strahler, 1987), multi-scale spatial variability (Myers, 1997), and Fractal analysis (Emerson et al., 1999). Several studies have explored spatial autocorrelation measures to examine the autocorrelation of pixel DNs and to determine the optimal spatial resolution of a remotely sensed application (Atkinson 1997).

2.3 Multi-scale classification decision rules and algorithms

Three strategies were developed for maximum likelihood classifier by Chen and Stow (2003) to exploit information obtained from different resolutions and thus, to improve the classification results.

The first strategy is a simple means of using information from multiple resolutions by incorporating them simultaneously in a classification routine. In this way feature measures obtained at various resolutions are merged. This approach is simple and no other algorithms are needed to organize the data. The major drawback is that computation cost may be high

The second strategy is to compare the posteriori probabilities obtained from different resolutions. For this approach, the classifier is applied at each resolution to obtain the probability for each pixel as a member of class. The probabilities are then converted to a posteriori probabilities of class membership, which are assessed as the probability density of a case for a class relative to the sum of the densities. For each pixel, the a posteriori probabilities sum to 1.0. At each resolution, the highest a posteriori probability and its related class are output for each pixel. With this approach, the feature layers obtained from coarse resolutions do not have to map back to the finest resolution specified and the computation cost is lower than that in the first strategy.

The third approach is a top-town filtering approach. This multi-resolution procedure starts with the coarsest resolution image. The finer resolution images are used only when necessary. The posterior probabilities of the training data are used to determine the threshold at each resolution level. For pixels with maximum posterior probabilities greater than the threshold are assigned to their related classes and are excluded (masked) for subsequent processing. All pixels with maximum posterior probabilities less than the threshold are regarded as mixed pixels, or pixels that do not have identical signatures and cannot be identified at this resolution level. Their posterior probabilities are used as prior probabilities at next resolution level.

More efficient classification algorithms can be used. This includes the Fuzzy-set and neural net classifiers (Foody, 1999; 2000), approximating the model by Markov, conditional independence or fractal structure obtained from multi-scale analysis (Solberg et al. 1996; Li et al. 2000).

2.4 Error analysis

At the same spatial resolutions, classification errors can be influenced by many factors, such as scheme selection, spatial autocorrelation among and within classes and classification techniques, to name a few. Traditionally classification error analysis is based on the use of an error matrix or contingency table to derive descriptive statistics such as overall accuracy, kappa coefficients, etc. The error models for area classification maps across scales are largely unsolved and little work has been done, although it is becoming more important with the increasing availability of multi-scale data (Tate and Atkinson 2001). The emphasis in this framework is to explore how spatial autocorrelation of classification errors among and within classes changes with spatial resolutions. The variance loss from fine resolution to coarse resolution will be calculated. The relationship between these errors and spatial autocorrelation parameters obtained from the multi-scale analysis will be analyzed for each class.

3. CASE STUDY

The multi-resolution framework was tested using simulated multi-resolution images derived from IKONOS data for a portion of the western part of Kingston City, Ontario, Canada. The IKONOS image has a spatial resolution of 4 m with four spectral bands. Ten land cover classes were used, including residential roof, industrial/commercial roof, Road, lawn, conifer tree, deciduous tree, bare/cleared land, water, new crop, and wetland.

4 m IKONOS image was aggregated progressively into four nominal resolution levels (8 m, 12 m, 16 m, and 20 m) by an averaging method. Both single-resolution and multi-resolution classification were conducted. The single-resolution classification was used as a benchmark for evaluating various multi-resolution approaches.

Initial exploratory data analysis was carried out as three trials. The first trial used histograms to determine the types of distribution exhibited by each band. The second trial included the mean and standard deviation to assess distribution properties. The final trial established if each band offers or similar or different information, i.e. are they correlated?

A set of sampling data was selected for each class. The semi-variogram was used in the case study to decide the spatial autocorrelation level in each class. Each value of a pixel was compared to its neighbors at varying distances (lags) and the differences were calculated. The semivariance was then calculated by averaging the summation of squared differences for pixels. In most cases the semivariance tends to increase with spatial intervals. After reaching a maximum value, the semi-variogram flattens (called the *sill*). The lag at which the sill is reached is called the *range*. The range indicates the extent to which values sampled from a spatial process are similar (spatially related). Detailed theoretical and mathematical exploration of variograms can be found in Cressie (1991), and Woodcock et al. (1988a; 1988b).

The non-directional or isotropic semi-variogram was calculated and plotted for to assess the degree of spatial autocorrelation in respective bands in the case study. The ranges were determined by visual examination and through a comparison of piecewise slopes. Table 1 lists the ranges for each class.

Classes	Range (m)
Residential roof	16
Commercial/industrial roof	28
Road	8
Lawn	14
Conifer trees	6
Deciduous trees	12
Cleared/bare land	30
Water	12
New crop	24
Wetland	8

Table1. The ranges obtained from semi-variogram

The shape and range of each semi-variogram were useful for determining suitable sizes for training data, sampling interval, resolution or window sizes used for spatial feature extraction. Based on the discussion in previous section, when image resolution is close to or coarser than the range of a class, an L-resolution scene model is generally most appropriate for that class. Otherwise, spatial features that incorporate texture/contexture information should be generated at H-resolution.

Training data were selected by visually identifying and manually digitizing blocks of pixels. As a general rule, the length and width of small blocks for each class were close to the range obtained from the semi-variogram, so that each block was big enough to represent the spectral and spatial properties of each class. Thus, the heterogeneity or autocorrelation within each class was included in the training data. The distance between any two blocks was greater than or equal to the range of the semi-variogram, so the pixels in one block were correlated, but not spatially autocorrelated with those in another block.

The strategy of comparing posterior probabilities from multiple resolutions was tested in the case study. For this approach, the classifier is applied at each resolution to obtain the probability P(k|i) for each pixel k as a member of class i (i=1, 2, …, m possible classes). The probabilities are then converted to a posteriori probabilities of class membership, which are assessed as the probability density of a case for a class relative to the sum of the densities (Jensen 1996). The a posteriori probability of a pixel k belonging to a class i, L(i |k), is determined by the following equation (1):

$$L(i\,|\,k) = \frac{a_i P(k\,|\,i)}{\sum_{i=1}^{m} a_i P(k\,|\,i)} \tag{1}$$

where $P(k|i)$ = the probability for a pixel k as a member of class i,
a_i = *a priori* probablity of membership of class i,
m = total number of classes.

For each pixel, the *a posteriori* probabilities sum to 1.0. At each resolution, the highest *a posteriori* probability and its related class are output for each pixel. $L_l(i|k)$ represents the maximum *posteriori* probablity of a pixel *k* belonging to class *i* at resolution level *l*, $L_l(i|k)$ derived from all resolutions and *k* is assigned to the class with the highest maximum *a posteriori* probability. Thus, *k* in class c, if and only if,

$$L(c|k) \geq L_l(i|k), \tag{2}$$

Where i = 1, 2, 3, …m possible classes,
l = 4m, 8m, … possible resolutions.

The results were evaluated and analyzed based on classification accuracy for eight land use/cover classes. A total of 600 randomly selected samples were identified for the study area. The overall and individual Kappa coefficients (Jensen 1996) were reported for the study area for a series of classification maps to evaluate the agreement between the classification results and the reference data.

To determine the difference between two kappa coefficients, the significance test proposed by Cohen (1960) for comparing two classification results was adopted. With this method, the difference between two Kappa coefficients resulting from two classifications was first obtained. The square root of the sum of the variances V_K between the two classifications was then calculated. A z-value is determined by dividing the difference by the square root. A z-value above 1.96 indicates that two classification results are significantly different at the 0.95 confidence level.

Table 2 presents the summarized results obtained from single-resolution and multi-resolution approaches based on their classification accuracies in discriminating between eight land use/cover classes. The Kappa coefficients obtained from classification using three multiple strategies are greater when compared to those from single resolution image input. Classification accuracy improvements are significant at the 0.95 confidence levels for the multi-resolution approach relative to comparable results from all single resolution classifications.

Resolution	Kappa
4 m	0.614
8 m	0.648
12 m	0.667
16 m	0.694
20 m	0.681
Multi-resolution	0.755

Table 2. Summary of classification accuracies derived from single-resolution and multi-resolution strategies. Accuracy is expressed as Kappa values.

4. SUMMARY AND CONCLUSION

One of the fundamental considerations when using remotely sensed data for land use/cover mapping is that of selecting appropriate spatial resolution(s). With the increased availability of very high resolution multi-spectral images spatial resolution variation will play an increasingly important role in the employment of remotely sensed imagery. The correct application of image classification procedures for mapping land use/cover requires knowledge of certain spatial attributes of the data to determine the appropriate classification methodology and parameters to use. In general, traditional single-resolution classification procedures are inadequate for understanding the effects of the chosen spatial resolution. They have difficulty discriminating between land use/cover classes that have complex spectral/spatial features and patterns. Although a number of different approaches have been developed for classifying highly heterogeneous landscapes, current research focuses on contextual, knowledge-based, and segmentation routines using spatial and spectral information. Most of approaches developed mainly for Landsat TM and SPOT HRV images are often scene specific and untested on high resolution images (1 m to 10 m).

The multi-resolution framework proposed in this paper recognizes that image classification procedure should account for image spatial structure to minimize errors, and increase efficiency and information extraction from the classification process. Selection of the training scheme and classification decision rules should be guided by specification of the type of scene model (H- and L- resolution) and level of spatial variance represented by the image to be classified.

The technical basis of the multi-resolution framework and its potential advantages over commonly used single-resolution classification procedures were introduced and discussed. A variety of approaches may be used to generate multi-resolution image data sets. Different spatial analysis methods can provides the above information to allow resolution effects on individual classes examined. Different strategies can be used to incorporate information from multiple resolutions.

The case study illustrated the potential of multi-resolution classification framework. Using a simulated multi-resolution data set and one multi-resolution strategy, it was demonstrated that multi-resolution classification approaches developed could significantly improve land use/cover classification accuracy when compared with those from single-resolution approaches. Multi-scale data analysis can provide useful information to ensure that subsequent classification methods and parameters are suited to the spatial characteristics of the features (or classes). The results confirm the validity and efficiency of the proposed framework.

This research is an initial step towards building an integrated multi-resolution image analysis and classification framework for land use/cover mapping using multiple spatial resolution and multispectral earth observation data. Further test in using real satellite data with different spatial resolutions will be conducted in different landscapes. The refinement, particularly of class structures and descriptors from spatial techniques, and exploration of how different spatial techniques can quantify resolution-dependent spatial characteristics of the image and can be used in the classification routine are required. More advanced classification approaches such as neural nets, fuzzy set classifiers, and expert classifier models will also be tested in the multi-resolution context in the future. Further research in multi-resolution error modeling to linking classification results across different spatial resolutions is also required.

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