A HYBRID APPROACH TO DETECTING IMPERVIOUS SURFACE AT MULTIPLE-SCALES

Stefan E. Coe, M. Alberti, J. A. Hepinstall, and R.Coburn

Urban Ecology Research Laboratory, Department of Urban Design and Planning, Box 355740, University of Washington, Seattle, 98195.

KEY WORDS: Impervious Surface, Ecological Processes, Object Oriented Classification.

ABSTRACT:
Detecting impervious surface in urban areas is critical to understanding the effects of urbanization on ecological processes. However, it presents unique challenges due to the spatial and spectral heterogeneity of the urban surfaces and the rapid changes in land cover that occur over short time periods. In this project, we develop a hybrid approach that combines an object-oriented and a pixel-based classification approach. Our approach integrates remotely sensed data – Landsat, Ikonos, and Lidar – and parcel data to develop a spatial database featuring urban object information at multiple spatial scales and class resolutions. Towards these objectives, eCognition™ software is used to perform image segmentation, nearest neighborhood classification, and the development of semantic rules incorporating object attribute information.

INTRODUCTION

Detecting impervious surface in urban areas is critical to understanding the effects of urbanization on ecological processes (Karr 1991, Schueler 1994, Horner et al. 1996). However, it presents unique challenges due to the spatial and spectral heterogeneity of the urban surfaces and the rapid changes in land cover that occur over short time periods (Hornstra, et al., 1999; Small, 2002). In this project, we develop a hybrid approach that combines an object-oriented and a pixel-based classification approach. Our approach integrates remotely sensed data – Landsat, Ikonos, and Lidar – and parcel data to develop a spatial database featuring urban object information at multiple spatial scales and class resolutions. The scope of the project is defined by four main objectives:

1. Assess which data are most appropriate for a given unit of analysis (e.g. sub-basin vs. parcel level);
2. Assess the ability of an object-oriented approach to classify urban objects (e.g. buildings, roads) at multiple spatial scales;
3. Determine to what extent fuzzy rules incorporating object attributes and spatial relationships can be used to determine general development types at the parcel scale; and
4. Test the effectiveness of Lidar data to provide additional information regarding the vertical structure of urban landscapes.

METHODS

Towards these objectives, eCognition™ software is used to perform image segmentation, nearest neighborhood classification, and the development of semantic rules incorporating object attribute information. For the Ikonos data, two levels of image-based segmentation, combined with parcel boundaries, are used to create a super scale, parcel scale and sub-parcel scale framework. General classes, including urban, rural and water, are created using classification-based segmentation to define large objects at the super scale. Finer scale objects, such as buildings, roads, trees, and patches of grass are then identified at the sub-parcel scale using semantic rules defined by object attributes at both the super scale and the sub-parcel scale. Lidar data is used to help separate buildings from other urban objects like parking lots and roads.

A similar approach is used to classify Landsat data, albeit with a more general classification scheme. In the Pacific Northwest, the most challenging aspect of classifying moderate resolution data, such as Landsat, in urban areas is separating pixels that are truly urban from pixels that have similar spectral properties like fallow agriculture and clear cuts. We hypothesize that using an object approach coupled with Lidar data averaged over the Landsat pixel will improve accuracy in separating urban pixels from other classes. Using the difference between first return data and bare earth elevation, Lidar data is used to help differentiate between different types of urban objects such as buildings, roads, forest canopy, and lawns. The composition and configuration of sub-parcel objects within the parcel boundaries is used to determine an urban development typology.

Data Sources

For this analysis we use a Landsat image from 07/21/2002 (path 26, row 46), which has been atmospherically and geometrically corrected. We use spectral unmixing to derive additional bands from the Landsat image including percent impervious surface and percent shade. For the same extent, Lidar data is acquired from the Puget Sound Lidar Consortium (PSLC). The Lidar data was processed by the PSLC into two digital elevation models (DEMs), representing top surface (first return data) and bare surface (last return data), each with an initial cell resolution of two feet. A surface difference layer, representing the vertical height of structures and natural objects, such as buildings and forest canopy, is created by subtracting the bare surface DEM from the top surface DEM. This layer is converted to UTM and given the same resolution as the Landsat data by averaging pixels values to a 30m regular grid. Finally, several Pan-sharpened Ikonos scenes of various urban areas in the Puget Sound region were acquired from Space Imaging.

Landsat Classification Steps

For the image classification, we employ eCognition™, an object-based image processing software tool. Within eCognition™, images are segmented using a region growing algorithm. The resulting segments or objects (polygons) are based upon band values (spectra) and user-defined parameters for object scale (object size), shape, and color (Baatz and Schape, 2000). The user can create several levels of segmentation in which finer-level objects are nested within larger-level objects, creating a hierarchy of image objects. For example, a given object in Level C can be related not only to its immediate neighbors within Level C, but also to the super object(s) that it belongs to (e.g., Levels A and B) as well as sub-objects that it is composed of (e.g., Levels D, E, F, etc.). This object-oriented approach allows for the development of a knowledge base whereby semantic rules can be used, in addition to the traditional classification techniques, to classify remotely sensed images (Baatz and Schape, 2000).

Using eCognition™, we specify two levels of segmentation using Landsat bands 2, 3, 4, 5, and 7, with scale parameters of 10 and 5. Sample objects are picked for urban, mixed-urban, grass, forest, soil, and water as training samples. Standard nearest neighbor (eCognition™'s supervised classifier) is used to classify the image into urban, mixed urban, grass, forest, soil, and water. The classification is evaluated based on digital orthophotography of the area. More sample objects are chosen for additional training in the case of confused classes (i.e., inaccurate classification) or unclassified objects. Classification-based segmentation is then used to merge the objects of the two levels. Urban, mixed urban, and soil are used from level 2 segmentation (scale parameter 10) and grass, forest, water from level 1 segmentation (scale parameter 5) to create one merged classification. These classes are then grouped into thre structure groups consisting of non-vegetation, vegetation, and water and classification based segmentation is used again to create super objects for these structure groups. Image segmentation is further used to produce two or more levels that are nested within the super scale image objects.

Non-Vegetation Classes: The standard nearest neighbor classifier and elevation rules are used to sub-divide the non-vegetation super objects into urban, soil, and clear-cut categories. In addition to the standard nearest neighbor classifier, a rule is applied so that soil and clear-cut objects cannot have an average surface height of over 8 feet. Objects that are classified as soil or clear-cut but have a surface height of over 8 feet are reclassified as urban. Although the opposite rule cannot be true for urban objects at finer scales, because of objects like parking lots that have little if no surface elevation, we apply a similar rule to urban objects at a segmentation layer with a high scale parameter (large objects). This is used to bring out large soil objects such as fallow agriculture or clear cuts. At this scale, urban features will contain some surface elevation due to buildings while fallow agriculture should exhibit little to no elevated features. Other semantic rules are developed for clear cuts such as the total area of neighboring forest objects and the length of border shared by non-urban objects. After rules have been applied, Urban objects are reclassified based upon the average impervious area per object that is derived from the percent impervious layer:

- 0-20% impervious
- 20-40% impervious
- 40-60% impervious
- 60-80% impervious
- 80-100% impervious

Vegetation Classes: Vegetation objects are separated into forest and grass using the Lidar surface height layer. If an object (at any level) is contained within a vegetation super object, then it is classified as grass, shrub, or crops if the average elevation per object is less than 10 feet or forest if over 10 feet. This category can easily be broken down into further categories including grass, agriculture, shrub, deciduous, and coniferous forest using similar techniques.

Water: Any object that is contained within a water super object remains water unless its elevation is greater than ten feet. Shade from buildings in areas such as downtown Seattle are often misclassified as water. This can easily be fixed by incorporating the surface height rule.

Ikonos Classification Method

Object based classifications are especially well suited for high-resolution imagery for several reasons. First, shaded pixels are often prevalent in high-resolution imagery and are difficult to classify because their spectral properties do not represent their true (un-shaded) spectral response. Similarly, individual or small groups of pixels are often not spectrally representative of the greater object they reside in, such as a pixels found in forest canopy gap, which maybe be classified as grass or soil in traditional classifications. In both cases, using an object approach gives the analyst the ability to assign these objects to their "true class" by using the topological and hierarchical relationships that are possible when using an image object approach.

The classification methodology for the Ikonos data follows the same general guidelines as the Landsat classification. The Lidar surface height layer is used in addition to the spectral data to add more information about the vertical structure of urban areas. The main difference is the types of rules that can be developed based upon the finer resolution of the data. For instance, building outlines are easily extracted from urban super objects using the Lidar data in conjunction with a segmentation scale appropriate for individual buildings. A major problem with high-resolution data is the number of pixels that are shaded and therefore have relatively little spectral information. Shade objects are classified along with urban, forest, grass, water, and soil using the standard nearest neighbor classifier. Similar, to the Landsat classification, classification-based segmentation is then used to merge the image objects of the individual classes to create super objects of non-vegetation, vegetation, water, and shade. Two more levels of segmentation are performed using scale parameters of 10 and 5. These layers are nested within the super objects and create a hierarchy of image objects. At this point, rules are developed and the super classes are sub-divided into categories of buildings, roads, parking, forest, grass, and soil. Shade objects are assigned to one of these classes based upon a series of proximity rules. For example, if a shade objects shares the majority of its border with a building object, then it is assigned as "building shade" and later reclassified as "building."

After the Ikonos classifications are complete, the composition of land cover inside individual parcels will be analyzed to see if rules can be developed to discern land use categories such as low, medium and high density residential, industrial, commercial, open space, etc.

Preliminary Landat Results

Our approach to both Landsat and Ikonos classifications is still under development. The combined effect of an object oriented approach and the addition of Lidar data is three-dimensional object information that has the potential to be especially effective in reducing errors of commission for urban classes. The vertical height information provided by the Lidar data assists in separating built-up urban features from non-urban classes like fallow agriculture and clear cuts. In addition, the three-dimensional information provided by the Lidar data has tremendous potential to reduce the feature space overlap that often exists between vegetation classes such as shrub and deciduous forest. A complete accuracy assessment will be performed comparing results to traditional classification methods.

Preliminary Ikonos Results

Using an object-based approach for high resolution data makes sense because it allows the analyst to incorporate contextual information for the assignment of pixels that are difficult to classify based on spectra alone (Baatz, 1999). Furthermore, the use of ancillary data such as Lidar provides additional three-dimensional information that is critical for detailed classifications. By providing the actual height of building objects, Lidar provides a greater ability to separate buildings from other urban objects, which is difficult using spectral data alone.

References:

Baatz, M., Schape, A., 1999. Object-Oriented and Multi-Scale Image Analysis in Semantic Networks. In: Proc. of the 2nd International Symposium on Operationalization of Remote Sensing, Enschede, ITC, August 16–20, 1999.

Baatz, M., Schape, A., 2000. Multiresolution Segmentation: an optimization approach for high quality multi-scale image segmentation. AGIT 2000. In: STROBL, J. et al., Proceedings of the Angewandte Geographische Informationsverarbeitung XII. Beiträge zum AGIT-Symposium Salzburg 2000, pp. 12-23.

Horner, R. R., C. W. May, E. H. Livingston, Maxted, J., 1996. Impervious Cover, Aquatic Community Health and Storm Water BMPs: Is there a Relationship? http://www.stormwater-resources.com/Library/090PLImpervious.pdf

Hornstra, P.M, Ventura, S. J., 1995. Incorporating intra-pixel reflectance variability in the multispectral classification process of high-resolution satellite imagery of urbanized areas, Cartography, 28(2): 1-9.

Karr, J. R., 1991. Biological Integrity: A Long-Neglected Aspect of Water Resource Management. Ecological Applications 1:66–84.

Schueler, T.R., 1994. The Importance of Imperviousness. Watershed Protection Techniques 1:100–111.

Small, C., 2002. Multitemporal Analysis of Urban Reflectance. Remote Sensing of Environment 81(2-3): 427-442.