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Geospatial Technologies in Your World

Feature Extraction: Getting the Most Out of Imagery

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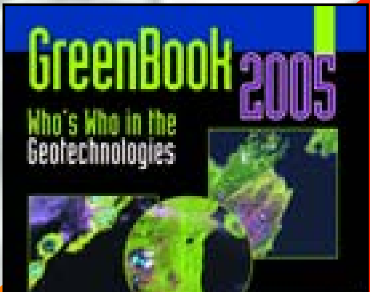

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Automated Processing of High Resolution Satellite Imagery

for Feature Extraction and Mapping of Urban Areas

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Introduction

High-resolution satellite imagery became commercially available in late 1999 with the launch of Space Imaging's IKONOS satellite. In subsequent years, several other high-resolution commercial satellites were launched (DigitalGlobe's QuickBird and ORBIMAGE's OrbView-3). The spatial resolution and spectral information provided by these sensors make them well-suited for urban area applications. The high spatial resolution (0.6-1m) allows the delineation of fine-scale features in the urban environment, such as individual roads and buildings.

Recently, the National Geospatial-Intelligence Agency (NGA) issued two separate $500M contracts to DigitalGlobe and ORBIMAGE for the development of next generation satellite sensors. These next generation sensors will have increased spatial resolution (~ 0.4 m) and additional spectral bands. Even with current imaging assets, the quantity of image data exceeds the human capacity of trained image specialists within the intelligence community to analyze. When data from the next generation sensors becomes available, the problem will get significantly worse. Automated upstream processing is needed to exploit the vast quantities of high-resolution commercial satellite data from current and next generation satellite sensors.

There are a number of commercial software packages, such as eCognition (Definiens Imaging) and Feature Analyst (Visual Learning Systems) that provide semi-automated processing capabilities. Semi-automated techniques require human interaction in the processing loop to input training data and/or control the operation of the software. Although semi-automated techniques can decrease the workload of image analysts, more automation in the processing chain is needed. Thus, the development of fully automated processing techniques, requiring no human interaction in the processing loop, is an active research area. This article summarizes several fully automated processing techniques developed for feature extraction and land cover classification over urban areas.

Urban Area Feature Extraction

The two most prominent features characterizing an urban environment are road networks and urban buildings. Both roads and buildings can exhibit a variety of spectral responses due to differences in age and/or material and vary widely in physical dimensions. Thus, these features are difficult to extract in an automated fashion due to their spatial and spectral variability within a scene and across multiple scenes.

In one approach we developed, road segments are extracted by first identifying groups of spectrally similar non-vegetation pixels oriented in a long narrow rectangular shape. An iterative algorithm then grows the ends of the line segments, extracting curved portions of roads (if present). As each road is extracted, it must fit a spatial model that enforces the road network topology. Vegetation is identified from the normalized difference vegetation index (NDVI) statistic calculated from the spectral image information and shape is quantified by a 2D spatial signature of the image pixels. The 2D spatial signature consists of the maximum and minimum length line segments of spectrally similar pixels passing through each non-vegetation pixel in the image. The process for computing the 2D spatial signature is illustrated in **Figure 1**. The output of the road extraction algorithm is a single pixel-wide piecewise linear response that estimates the location of the road centerline.

Although buildings vary significantly in size and spectral response, there are several characteristics common to most buildings that can be exploited for automated extraction. First, buildings cast shadows on the ground. Second, buildings in urban areas typically are quasi-rectangular in shape. Because there is significant variation in size, a multi-scale approach must be utilized. A multi-scale image decomposition technique can be used to identify bright and dark objects in an urban image. Bright and dark objects identified at one scale of a multi-scale decomposition are shown in **Figure 2**. Buildings with a bright spectral response as well as building shadows are easily visible in the decomposition. Two building detectors are utilized, direct detection of spectrally bright buildings through shape analysis, and indirect detection of buildings through identification of cast shadows.

The output of the fully automated road network and 2D building footprint extraction techniques for a dense urban area is

Figure 1 *2D spatial signature determination for a single road pixel. Left: line segments radiating out from central pixel are examined for spectral similarity. Right: maximum and minimum length line segments identified.*

shown in **Figure 3**. Accuracy measures for the extraction are reported in **Table 1**. The accuracy measures are calculated by comparing the automatically extracted features to ground truth reference features. Completeness is the percentage of the reference features that have been extracted by the automated processing, and Correctness is the percentage of the automatically extracted features that are not in error. It is important to report both statistics when analyzing feature extraction results. For example, if the entire image is identified as building, the extraction would be 100% complete but have a very low value of correctness. Conversely, if only a single road is extracted and it is correct, there will be 100% correctness but a very low completeness value.

Fully Automated Urban Land Cover Classification

Supervised classification techniques, such as maximum likelihood, are widely used for generation of land cover maps from remote sensing imagery. These classifiers require human generated training data and are thus only semi-automated. However, by automating the generation of training data, supervised classifiers can be used in an unsupervised, or self-supervised fashion, to perform urban land cover classification. Fully automated feature extraction techniques can be used to generate training data for input into supervised classification algorithms, thereby producing a self-supervised urban land cover classifier. Here, the feature extraction techniques do not seek to extract all features present in the imagery. Instead, they are used to identify very high confidence instances of the different urban land cover classes, so as to minimize the use of erroneous training data in the classifier.

Due to the complex nature of high-resolution urban area imagery, traditional classification techniques achieve only limited success in these areas. We previously developed a supervised fuzzy logic based classifier that was designed specifically for high-resolution urban imagery. In addition to spectral signature, the classifier makes use of a variety of spatial measures, selectively applying them only to the classes where they increase discrimination. The classifier operates at both the pixel and object levels, outputting a detailed urban land cover classification map. The identified urban land cover classes are: Road, Building, Impervious Surface, Grass, Tree, and Shadow.

Although our initial classifier was supervised, we can automatically generate the training data using feature extraction

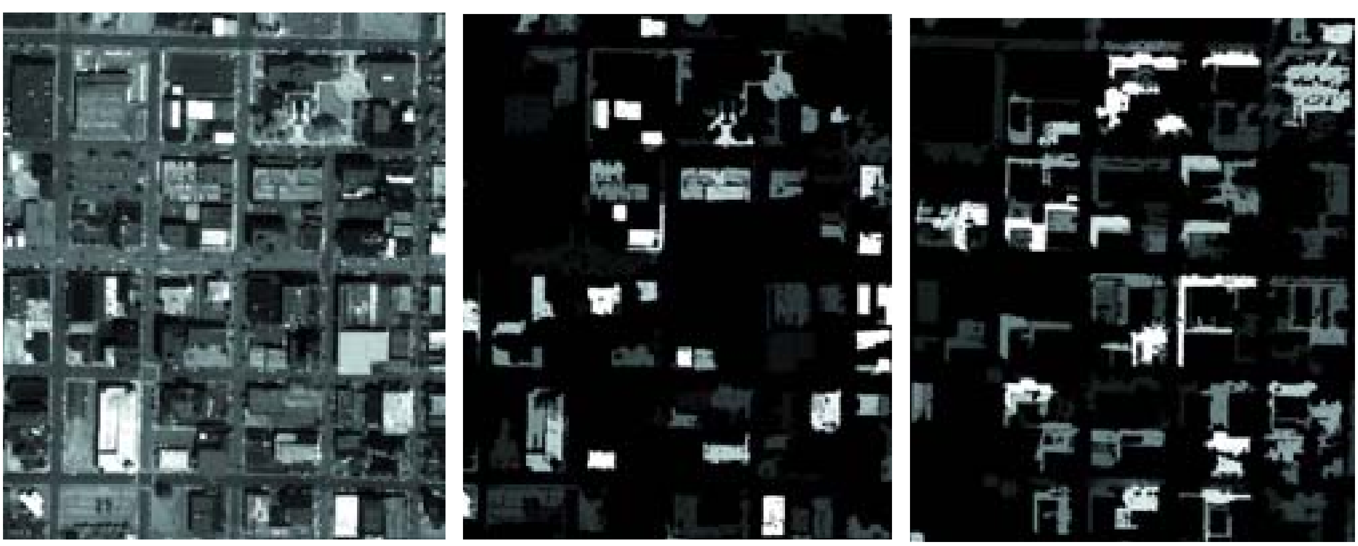

Figure 2 *Image decomposition. Left: panchromatic image; middle: bright objects; right: dark objects. Note: Only one scale of the multi-scale decomposition is shown here.*

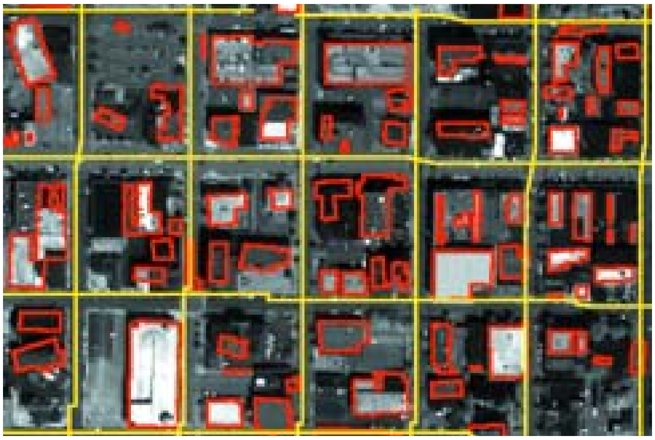

Figure 3 *Extracted road network and 2D building footprint features*

methods so that no human input is required. Because labeled training data is generated internally by the system, systems of this type can be referred to as self-supervised. Self-supervised classification systems differ from unsupervised classifiers in that unsupervised classifiers output an unlabeled classification, requiring further human analysis to determine the class labels, whereas self-supervised classifiers output a labeled classification.

Feature Extraction Statistics ***(Urban Image, Figure 3)***

	Completeness	***Correctness***
Road Network	**87.2%**	**70.4%**
2-D Building Footprint	**70.7%**	**87.4%**

Modified versions of the feature extraction algorithms described in the previous section are used to generate training data for the Road, Building, and Shadow classes. Training data for the vegetation classes are generated through analysis of the NDVI statistic and an entropy texture measure. No training data is required for the Impervious Surface class. The urban land cover map generated using this fully automated self-supervised classification approach is shown in **Figure 4**. The classification has an overall accuracy of 87%, extremely good for a fully automated technique. The individual class accuracies are reported in **Table 2**.

Urban Land Cover Classification Accuracies
(Land Cover Image, Figure 4)

Class	***Accuracy***
Road	**95%**
Building	**70%**
Impervious Surface	**72%**
Grass	**100%**
Tree	**99%**

Future Work

Although the results achieved thus far are promising, there remains much work to be done in the development of fully automated processing techniques for urban area mapping and feature extraction. Specifically, additional work must be done on the self-supervised classifier to increase the accuracy of the Building and Impervious Surface classes. In addition, when the next generation satellites from DigitalGlobe and ORBIMAGE become available, these techniques will need to be extended to take advantage of the increased spatial and spectral resolutions.

About the Authors

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Figure 4 *Self-supervised urban land cover classification. Left: false color image; right: urban land cover map*