OBJECT-ORIENTED CLASSIFICATION: CLASSIFICATION OF PAN-SHARPENING QUICKBIRD IMAGERY AND A FUZZY APPROACH TO IMPROVING IMAGE SEGMENTATION EFFICIENCY

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PREFACE

This technical report is a reproduction of a thesis submitted in partial fulfillment of the requirements for the degree of Master of Science in Engineering in the Department of Geodesy and Geomatics Engineering, September 2005. The research was supervised by Dr. Yun Zhang, and support was provided by the Department of National Defence.

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ABSTRACT

Today's very high spatial resolution satellite sensors, such as QuickBird and IKONOS, pose additional problems to the land cover classification task as a consequence of the data's high spectral variability. This problem is further emphasized in the use of fine resolution pan-sharpened imagery in the place of coarser multispectral data for land cover classification. To address this challenge, the object-based approach to classification demonstrates considerable promise.

In general, it is claimed that the object-oriented classification methodology is better able to deal with highly textured data. Consequently, we hypothesize that an object-oriented approach is better suited to reveal the true benefits of fused imagery over original multispectral data in land cover classification. In pursuit of this goal, we propose to use eCognition, an object-oriented classification application developed by Definiens Imaging, to test the classification accuracy achievable using both original multispectral and UNB Pan-Sharpened QuickBird imagery.

Furthermore, the success of the object-oriented approach remains highly dependent on the successful segmentation of the input image. Image segmentation using the Fractal Net Evolution Approach has been very successful by exhibiting visually convincing results at a variety of scales. However, this segmentation approach relies heavily on user experience in combination with a trial and error approach to determine the appropriate parameters to achieve a successful segmentation. This thesis proposes a fuzzy approach to supervised segmentation parameter selection to optimize the selection of segmentation

parameters in a time efficient manner.

Results demonstrate that UNB Pan-Sharpened imagery offers a noticeable visual improvement over classification with original multispectral data. In addition, testing of the fuzzy segmentation parameter selection tool demonstrates significant promise to improve the object-based classification workflow. This improvement is realized by producing excellent segmentation results in a highly efficient manner suitable for the first time user without an understanding of the underlying segmentation process.

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Chapter 1

Introduction

I think the major challenge is…the mounting and increasing demands, in our case, for volume, for accuracy, for currency, for completeness, rapid turn around, rapid update – everything's got to be done faster and faster and faster with greater and greater accuracy and currency.

[James R. Clapper Jr., Director NGA]

1.1 Rapid Advancement in Sensor Technology

Launched in September 1999, Space Imaging's IKONOS satellite ushered in the modern era of very high spatial resolution (VHR) earth observation. Demonstrating the capability to capture one metre panchromatic and four metre multispectral imagery, this achievement quickly had far reaching effects through a broad spectrum of applications. Today, IKONOS is only one of a growing number of VHR space-borne sensors including DigitalGlobe's QuickBird and OrbImage's OrbView-3. Through the emergent collection of orbital platforms providing competition and keeping prices reasonable, VHR satellite imagery has seen widespread use by government, industry, and scientific communities. However, limitations on their application also persist as processing techniques endeavor to keep pace with the rapid improvement of sensor technology.

Striving to maintain its leadership status in the global market, the United States government is heavily investing in the commercial remote sensing sector. The United States Commercial Remote Sensing Policy instituted in April 2003 seeks to foster further development of commercial remote sensing technologies to meet government requirements and keep the competitive edge in the global marketplace [Office of Science and Technology Policy, 2005]. Improved spatial resolution is one of the key requirements in this development.

To meet government imagery and geospatial needs, next generation sensors will have the capability to collect at least 0.5 metre panchromatic and 2.0 metre multispectral imagery. Scheduled for orbit within the next two years, DigitalGlobe's next generation WorldView satellite and OrbImage's OrbView-5 satellite are two examples of this capability [DigitalGlobe, 2005; OrbImage, 2005]. Together, these sensors demonstrate the technological innovation that will continue to challenge the automated processing of high spatial resolution imagery into the foreseeable future.

1.2 Current Trends and Problems for Land Cover Classification

Image analysis conducted by the human analyst is quickly becoming less viable given the quantity and currency requirements of data being managed in today's geographic information systems (GISs). Increasingly important are accurate automatic methods for information extraction. In particular, automatic land cover classification of satellite imagery is considered fundamental and critical to the information extraction problem [Swiewe et al., 2001; Huiping et al., 2003]. To a large degree, problems encountered using automatic per-pixel land cover classification techniques are a result of the trend toward higher spatial resolution sensors. These problems are well documented in literature [see Aplin et al., 1999; Schiewe et al., 2001; Schiewe, 2002; Huiping et al., 2003; Carleer et al., 2005; Frauman and Wolff, 2005].

In general, the intent of classification "is to replace visual analysis of the image data with quantitative techniques for automating the identification of features in a scene" [Lillesand and Kiefer, 1994]. This task is often carried out through the use of pixel-based classification techniques that rely on the spectral pattern of individual pixels to label them with the appropriate land cover class in a supervised or unsupervised manner. Supervised classification relies on the analyst training the classification system through the choice of representative pixels for each land cover type. Unsupervised classification statistically groups spectrally similar pixels in clusters that the user must then identify and label as representing a particular land cover class. Both methods see wide use today.

The trend toward higher spatial resolution sensors is challenging these traditional methods for a number of reasons. First, pixels in VHR imagery represent individual components of land cover objects and often these components exhibit varying degrees of reflectance [Baschke and Strobl, 2001; Ehlers et al., 2003]. As an example, modern sensors are able to detect individual objects on a rooftop such as skylights, heating and cooling units, shadows, and different building materials. Each object has its own characteristic reflectance and the result is a high degree of texture within a specific land cover class. This complicates classification based solely on pixel spectral properties.

Secondly, VHR data has a characteristically high panchromatic spatial resolution and significantly lower resolution in the multispectral bands. This lack of detail in colour imagery has led to the development of a number of new image fusion algorithms that combine these images to produce a higher resolution result [Genderen and Pohl, 1994;

Pohl and Genderen, 1998]. The advancements achieved in this area are remarkable and it is reasonable to expect that research into new pan-sharpening techniques will continue so long as resolutions differ between panchromatic and multispectral data sets. However, the application of pan-sharpened data to the classification task is relatively unproven.

Thirdly, there exists an unavoidable tradeoff between spatial and spectral resolution of a space-borne sensor. As the sensor's instantaneous field of view (IFOV) decreases, the spectral resolution is limited owing to the requirement to maintain an adequate signal to noise ratio. The result is the relatively weak spectral resolution that is characteristic of current VHR sensors [Munechika et al., 1993; Carleer et al., 2004]. Combined, pixel variability from original or pan-sharpened data sets and weak spectral resolution make per-pixel classification methods increasingly inadequate as the spatial resolution continues to improve into the next generation of sensors.

1.3 Object-Oriented Classification

To permit automated processing of imagery captured by modern sensors, new methods are being developed to intelligently manage these attributes. Emphasizing the need to take advantage of information beyond that provided in the spectral domain by arbitrarily defined pixels, these new methods use spatial pattern recognition techniques to augment spectral-based classification procedures. Object-oriented classification shows promise in this regard.

The arbitrary spatial units that form an image are a direct consequence of the sensor's IFOV. The pixels are arbitrary in the sense that they are characteristic to the sensor and have no relationship to the scene content or topology. For remotely sensed imagery, this trait represents a specific case of the Modifiable Areal Unit Problem (MAUP) whereby there exists a vast number of combinations through which an image can be divided and analyzed [Openshaw and Taylor, 1979; Marceau, 1999; Marceau and Hay, 1999, Hay et al., 2003]. Although a number of solutions to this problem have been proposed, the use of pixels grouped into meaningful image objects "represents the clearest way out of MAUP, as an analyst works with spatially discrete entities rather than arbitrarily defined areal units" [Hay et al., 2003]. In this way, meaningful topological objects exhibit characteristic texture, shape and contextual features, which can be used to augment spectral features and result in a better overall classification.

Object-oriented classification, therefore, is an approach aimed at solving the problems encountered using per-pixel classification methods on VHR imagery [Definiens Imaging GmbH, 2004a]. Generally, two steps are needed in object-oriented classification: (1) segmentation, and (2) classification. Segmentation involves partitioning the image into contiguous groups of pixels called objects. Ideally, these objects correspond to real world objects of interest [Hofmann and Reinhardt, 2000]. Once the objects have been identified within the image, the second step commences with the classification of these objects based on spectral, textural, size, shape, and contextual features. In the end, the use of successfully segmented images may lead to improved classification accuracy when compared to pixel-based classification methods [Janssen and Molenaar, 1995; Aplin et al., 1999; Carleer et al. 2004].

1.4 Existing Problems and Limitations

1.4.1 Pan-Sharpened Data for Classification

Pan-sharpening as a pre-processing technique used to condition data prior to classification has seen increased use in recent years [see Bauer and Steinnocher, 2001; Meinel et al., 2001; Neubert, 2001; Davis and Wang, 2002; Shackelford and Davis, 2003]. In fact, Hofmann [2001] goes so far as to recommend pan-sharpening as a useful pre-processing step prior to classification using the object-oriented methodology. However, very limited literature was found that actually evaluates the effect of pan-sharpening on the classification accuracy of the result.

In the context of the MAUP, a number of studies examined the effect of resolution on classification accuracy using pixel-based techniques [see Latty and Hoffer, 1981; Markham and Townshend, 1981; Cushnie, 1987]. The general conclusion was that spatial resolution could have a significant effect on classification accuracy with a general trend toward lower accuracy with increasing pixel resolution [Marceau and Hay, 1999]. Consequently, pan-sharpened data cannot be directly compared to original data by means of pixel-based classification techniques. For this reason, an approach based on common object scales (degree of object abstraction) is much more appropriate for comparative purposes. This approach will be used in this research to examine UNB Pan-Sharpening as a pre-processing technique for object-based classification.

1.4.2 Classification of Geographic Entities

As object-oriented techniques continue to evolve, some problems persist in their implementation that limit their full potential from being realized. One of the major limitations is the concept of segmentation at optimal scales. Humans have a natural ability to perform this cognitive task through the grouping of pixels into meaningful objects. The difficulty arises when we try to define automatic techniques to perform this function. Deducing the optimal scales and selecting those scales that are most appropriate to form a classification hierarchy are key problems in the realization of the multi-scale object-based approach [Hay et al., 2003]. Further complicating this issue is the lack of a theory that indicates the sensitivity of classification results to the scale of analysis [Burnett and Blaschke, 2003]. These issues currently restrict the operationalization of this approach.

Of the segmentation approaches that have been developed and employ the multi-scale methodology, few are available commercially and even less provide convincing results. In fact, an empirical investigation conducted by Neubert and Meinel [2003] reported that eCognition, by Definiens Imaging GmbH, demonstrated the best overall results in a comparison with a number of other segmentation schemes. Employing the Fractal Net Evolution Approach (FNEA), eCognition has been successful in providing realistic and visually convincing image objects in a number studies and over a variety landscapes [see Blaschke and Strobl, 2001; Schiewe et al., 2001; Hay et al., 2003].

While successful in many respects, FNEA requires that the user define the segmentation parameters for each desired scale. The user must simultaneously consider spectral, shape, and textural features and conduct extensive experimentation in order to achieve the desired scale segmentation [Hay et al., 2003]. Frauman and Wolff [2005] attempted to establish a rule between object size and object scale to simplify the parameter selection problem, but even though a link has been established, the rule remains elusive. Therefore, the parameter selection problem continues to limit this technique. In this research, we propose that a parameter selection method based on fuzzy logic could operationally enhance the FNEA technique by relying on a user's visual perception to delineate the objects of interest at a particular scale.

1.5 Objectives

The main objectives of this thesis are:

a. To evaluate the capacity of object-oriented classification to manage VHR imagery, including a comparison of pan-sharpened and original multispectral images; and

b. To develop a supervised fuzzy approach to improve the efficiency of segmentation in the object-oriented classification workflow.

A number of important tasks support the achievement of these main objectives. In support of the first objective, these tasks are:

a. To compare the effect of pan-sharpened imagery and original multispectral data on segmentation and classification;

b. To establish the most effective channels (panchromatic, blue, green, red, and/or near infrared) for successful segmentation; and

c. To determine the most appropriate data for object-oriented classification (original multispectral or pan-sharpened) based on visual assessment and statistical analysis.

The tasks supporting the achievement of the second objective are:

a. To outline the requirement for a system to guide the segmentation process within an object-oriented classification workflow;

b. To determine the applicability of a fuzzy logic control structure to the problem of segmentation parameter selection;

c. To define appropriate fuzzy variables by which to measure the state of segmentation within a system;

d. To develop a fuzzy inference system to guide the segmentation process with supervision; and

e. To qualitatively evaluate and compare the results of segmentation achieved with and without the fuzzy inference system based on the improved simplicity and efficiency of the proposed technique.

1.6 Thesis Outline

The material presented in this thesis is divided into eight chapters. To maintain a progressive and logical approach, chapters providing the theoretical background necessary to understand the technical developments and results will always be provided in advance of such discussion.

The introduction comprises the first chapter. This chapter sets the stage as a snapshot of where remote sensing technology is today with a look into the near future. The impact of recent technological advancement on land cover classification is discussed leading to the objectives of this research. The chapter closes with a brief outline of the thesis.

The second chapter outlines the methodology employed to complete this project. This chapter proceeds to outline VHR sensor characteristics and data used to conduct this research. The chapter ends with a discussion of important limitations and constraints identified during the conduct of this project.

Chapter three covers the theoretical background of object-oriented classification and its application to VHR multispectral and pan-sharpened imagery. This chapter will begin with the subject of image fusion and its application to the classification problem. Image fusion will be covered in general terms followed by a brief discussion of University of New Brunswick (UNB) Pan-Sharpening. With this background, the discussion will shift to emphasize object-oriented classification. This research implements object-oriented classification using eCognition, an application developed by Definiens Imaging GmbH. Primarily, segmentation will be the topic of importance since this is the key task that determines, to a large degree, the overall classification success and is essential to our discussion in follow on chapters. The chapter will close by covering the process of classifying objects by means of fuzzy membership in eCognition.

Implementation using multispectral and pan-sharpened data sets will be the topic of chapter four. This chapter will begin with segmentation followed by classification of these data sets. Specifically, segmentation problems incurred during implementation will be identified and discussed in detail.

Based on segmentation problems identified during classification, the fifth chapter will develop a fuzzy tool to improve the efficiency of segmentation parameters in eCognition. The theory of fuzzy logic as a control structure will be covered and will specifically highlight the application to our problem of segmentation parameter selection. To facilitate understanding of the proposed tool, fuzzy logic will be discussed in detail to include basic set theory, fuzzy variables, fuzzy sets, fuzzy operators, rule bases, implication, aggregation, and defuzzification all within the context of a fuzzy inference system (FIS). Having covered the necessary background theory, the new technique will be developed and explained commencing with the creation of the workflow for segmentation parameter determination. Finally, using this workflow as a guide, we will logically progress through the problem of FIS development.

Chapter six will implement the new fuzzy tool developed in this research. The imagery used for this implementation phase will focus on pan-sharpened imagery due to its characteristically high spatial resolution. A number of different land cover types will be tested to examine the success and robustness of the system.

Chapter seven will focus on the results achieved. This chapter will begin with a comparison of pan-sharpened and original multispectral classifications. Following this comparison, the segmentation results achieved using the proposed fuzzy logic tool for segmentation will be discussed and assessed. Improvements over the previously available methods will be highlighted and graphical results in both cases are compiled here to augment the discussion.

Chapter eight will draw conclusions based on these research results and will end by formulating recommendations for future research in this subject area.

Chapter 2

Project Overview

While numerous segmentation strategies and variants have been proposed,…the tailoring of segmentation parameters to expected scene thematic content is critical and holds more promise for improved performance than the search for new segmentation and edge detection methods.

[Matsuyama, 1987; Guindon, 1997]

The main objectives of this research are twofold: (1) to evaluate the capacity of object-oriented classification to manage VHR imagery, including a comparison of pan-sharpened and original multispectral images, and (2) to develop a supervised fuzzy approach to improve the efficiency of segmentation in the object-oriented classification workflow.

Relating to the first objective, Section 2.1 will discuss the concept of pan-sharpening, the essential properties for its application to the classification problem, and the recent development and success of UNB Pan-Sharpening. Section 2.2 will discuss the different approaches to classification and evaluate the most appropriate method to examine the applicability of pan-sharpened data to the classification problem. With the emphasis in this research on the object-based approach, the concept of segmentation will be covered in Section 2.3 leading to an overview of the parameter selection problem and the second objective of this research. Finally, having discussed the research aims, we will proceed to outline VHR sensor characteristics as background relating to the source of our data (Section 2.4), the data set and software used (Sections 2.5 and 2.6), and finally the constraints and limitations encountered during the course of this project (Section 2.7).

2.1 Pan-Sharpened Imagery for Land Cover Classification

"Image fusion is the combination of two or more different images to form a new image by using a certain algorithm" [Genderen and Pohl, 1994]. In the context of this research, we are specifically interested in the fusion of panchromatic and multispectral imagery acquired by VHR satellite sensors such as IKONOS or QuickBird. These techniques are particularly attractive since they allow the user to preserve the spatial detail characteristic of the panchromatic channel while retaining the spectral information of the original multispectral bands. The result is colour imagery with the same spatial resolution as the panchromatic image. The use of fine resolution pan-sharpened imagery in the place of coarser multispectral data is an attractive option for land cover classification and a technique that is seeing increased use as new image fusion algorithms are developed. However, there is little research that examines the applicability of this data to the classification problem.

For the purpose of classification, fusion techniques that maintain the radiometric characteristics of the imagery are of primary interest [Munechika et al., 1993]. Although pan-sharpening methods based on the separation of spectral and spatial components (ie. principal component analysis) have been used for classification, an examination of their classification suitability could not be found in literature. A visual evaluation of this category of techniques often presents a degree of colour distortion and raises the question of suitability in this regard. Munechika et al [1993] suggest that techniques "more statistically rigorous in its attempt to maintain radiometric fidelity" are required.

In 2002, the University of New Brunswick (UNB) patented a new automatic fusion method called UNB Pan-Sharpening. By employing a least squares approach, this automatic method has produced convincing results as to the spectral integrity of fused VHR imagery [Zhang, 2002; Cheng et al, 2003]. To date, this method has been incorporated into PCI Geomatica as well as Digital Globe's production line. Given the recent success of this technique based on its visually convincing result and backed by the statistical rigor of least squares, this approach offers sound classification potential. As a result, UNB Pan-Sharpening will be the fusion method evaluated in this research.

2.2 Classification Approaches

2.2.1 Pixel-Based Classification

Through the use of pixel-based classification methods, it is very difficult to assess whether or not classification results using pan-sharpened imagery are superior to those using the original data set. This difficulty exists for four reasons: (1) different resolutions between original and pan-sharpened data sets, (2) uncertainty of spectral integrity, (3) high pixel variability, and (4) MAUP.

In the first instance, comparison of classification accuracies is difficult when using imagery of different resolutions. In the case of QuickBird this means comparing the classification of 2.8 metre original multispectral and 0.7 metre pan-sharpened imagery. Classification accuracy is resolution dependent and no single resolution is ideal for all land cover classes [Marceau and Hay, 1999; Huiping et al., 2003]. As a result, we would expect to see accuracy improvement in some classes while degradation in others. This would not allow for a meaningful basis of comparison.

Secondly, the spectral integrity of UNB Pan-Sharpened imagery is relatively unproven. Although visually convincing and mathematically rigorous, we must establish the suitability of the spectral properties of pan-sharpened imagery to the classification task. This remains difficult to perform without first controlling the effects of different resolutions. For example, if the classification accuracy of a given land cover class is worse using pan-sharpened imagery, it is difficult to deduce if the degradation should be attributed to the resolution difference or lack of spectral integrity.

Thirdly, traditional pixel-based classification techniques have an inherent difficulty dealing with the high information content resulting from the high spatial resolution of modern satellite sensors. This problem is further emphasized when classifying pan-sharpened multispectral imagery as a result of the increased spectral variability over the original multispectral data. Often this difficulty becomes apparent in the so-called salt and pepper effect of the classified image.

Finally, and most importantly, the pixel-based approach does not address the modifiable areal unit problem. Therefore, to address all these issues and reveal the true benefits of UNB Pan-Sharpened imagery, this research will employ the object-oriented approach to land cover classification.

2.2.2 Object-Oriented Classification

Approaching our classification problem using the object-oriented methodology, implemented in this research through FNEA, classification can be carried out at similar object scales. By examining and comparing similar sized objects in both the original multispectral and pan-sharpened data sets, we will alleviate the problems associated with comparing classifications at different resolutions. This will, in turn, permit the examination of the spectral integrity of the fused imagery and its applicability to the classification problem. Although work-around pixel-based solutions could be implemented to permit a comparison of the results (ie. resampling), the object-oriented methodology will permit us to carry out the classification in a manner better suited to modern VHR sensors and highly textured data while addressing the MAUP.

2.3 Segmentation

Segmentation is the division of an image into "its constituent parts and extracting these parts of interest (objects)" [Zhang, 1996]. The algorithms by which segmentation is carried out have been the focus of significant research in the past two decades [Zhang, 1997; Carleer et al., 2004]. Using the object-oriented approach, only a successfully segmented image will lead to a convincing classification. In general, these algorithms can be classed into two distinct categories: boundary-based and region-based [Gonzalez and Woods, 1992; Janssen et al., 1995; Zhang, 1997; Carleer et al., 2004]. Boundary-based algorithms depend on the detection of contours through discontinuity in gray levels within the image. On the other hand, region-based algorithms associate pixels with similar characteristics into contiguous regions [Zhang, 1997; Carleer et al., 2004]. Regardless of the category, many segmentation algorithms rely on user selected parameters to perform the segmentation. The appropriate selection of these "parameters (thresholds) is very important and has a great influence on the segmentation results" [Carleer et al., 2004].

2.3.1 Segmentation Control

Control of the segmentation process can be classed as image-driven or knowledge-driven depending on the method by which the segmentation parameters are determined [Guindon, 1997; Definiens Imaging GmbH, 2004b]. Image-driven segmentation, also called "bottom-up control", begins at the pixel level and extracts contiguous objects across the entire image based on image features. Knowledge-driven segmentation, or top-down as it is also known, relies on the establishment of a model by which to extract corresponding objects. Both systems have their own advantages and disadvantages but a hybrid system using the strengths of each will undoubtedly prove the most effective [Guindon, 1997]. This research will implement a hybrid approach by establishing an object model to guide the selection and refinement of image segmentation parameters in the context of a region-growing algorithm.

2.3.2 Segmentation Parameter Selection

The motivation for this research originates from the requirement that many segmentation algorithms need some degree of user input for the segmentation of an image. Take the case of image segmentation using a thresholding technique. In this example the user must determine the appropriate threshold in order to achieve the best results for a given application. Consequently, a common approach to determine these parameters is trial and error until a satisfactory result is achieved. Further compounding this problem is a vague understanding of what result constitutes 'satisfactory' segmentation and how best to measure it [Zhang, 1997]. Unfortunately, without a systematic form of segmentation control, trial and error is inherently a very time-consuming process, especially when the analyst continues to apply this approach without a clear definition as to when he should cease his efforts.

Faster and more sophisticated methods to determine segmentation parameters are required to improve segmentation results in modern imagery characterized by very high spatial resolution and increased texture. In pursuit of this goal, we hypothesize that a control structure based on fuzzy logic is well suited to this task owing to its ability to manage vague input and deliver a definite result. Since successful segmentation is essential to achieving a convincing classification, this research will develop and implement a supervised fuzzy methodology to guide the segmentation process in eCognition with a view to decreasing time required for parameter selection, improving segmentation and increasing classification accuracy.

2.4 Sensor Characteristics

Data for this project relied on QuickBird imagery. Nevertheless, imagery from any of today's VHR sensors experience the common problems associated with classification owing to their high information content and relatively weak spectral resolution. For comparison purposes characteristics for QuickBird and IKONOS, together providing some of the highest resolution imagery currently available on the commercial market, are outlined in Table 2.1.

Table 2.1
Characteristics of QuickBird and IKONOS [DigialGlobe, 2004; Space Imaging, 2004]

Characteristic	**QuickBird**			**IKONOS**		
Inclination	98 degrees; sun-synchronous			98.1 degrees; sun-synchronous		
Altitude	450 km			680 km		
Period	93.4 minutes			98 minutes		
Revisit Rate	3.5 days			3 days		
Bands	Spectral Range (nm)	GSD (m)	Radiometric Resolution (bits)	Spectral Range (nm)	GSD (m)	Radiometric Resolution (bits)
Panchromatic	445 - 900	0.70	11	450 - 900	1.00	11
Multi-spectral (Blue)	450 - 520	2.80	11	450 - 520	4.00	11
Multi-spectral (Green)	520 - 600	2.80	11	510 - 600	4.00	11
Multi-spectral (Red)	630 - 690	2.80	11	630 - 700	4.00	11
Multi-spectral (Near IR)	760 - 900	2.80	11	760 - 850	4.00	11

2.5 Data Set

This research used QuickBird basic imagery. Data of this type is the least processed of all of DigitalGlobe's imagery products with only radiometric, internal sensor geometry, optical, and sensor distortions corrected [DigitalGlobe, 2004]. The minimal processing of this imagery was crucial to maintaining the original radiometric properties of the imagery as much as possible. This was particularly important for both the image fusion and classification problems.

The images that were selected included one rural and one suburban scene. The rural scene was selected because of its relative simplicity, while the suburban scene was selected due to its complexity. In this manner, the success of the classification methodology could be established for different types of image content. In addition, each of these scenes provided a broad spectrum of land cover types by which to evaluate the success of the segmentation parameters determined by the proposed parameter selection tool.

The first image (Figure 2.1) shows a rural scene located approximately 50 km southeast of Fredericton, New Brunswick, Canada, in the training area of Canadian Forces Base Gagetown. The second image (Figure 2.2) is the suburban scene centered on the town of Oromocto, New Brunswick, Canada. Specific details relating to these scenes are outlined in Table 2.2.

Table 2.2
Project metadata

Data Set	Sensor	Acquisition Date	Acquisition Time	Size
Rural	QuickBird	26 July 2002	15:21 UTC	3.2km x 2.6km
Suburban	QuickBird	08 August 2002	15:16 UTC	3.2km x 2.6km

Figure 2.1
Original multispectral QuickBird image of rural study area

Figure 2.2
Original multispectral QuickBird image of suburban study area

Georeferencing was not carried out on this imagery to avoid the resampling effects associated with this procedure. Instead, we chose to leave this processing step to the end of the classification process. In each case, the multispectral imagery was registered to the panchromatic layer. Once completed, the two scenes were subsequently pan-sharpened using PCI Geomatica's Pan-Sharpening module. Subsets of the original multispectral (Figures 2.3 and 2.5) and pan-sharpened results (Figures 2.4 and 2.6) are shown below.

Figure 2.3
Rural area subset of original multispectral QuickBird image

Figure 2.4
Rural area subset of pan-sharpened QuickBird image

Figure 2.5
Suburban area subset of original multispectral QuickBird image

Figure 2.6
Suburban area subset of pan-sharpened QuickBird image

To test the parameter selection tool developed in the second part of this thesis, subsets were selected from the pan-sharpened suburban data set. Each subset was selected to focus on a particular land cover class. These subsets are identified in Figure 2.7.

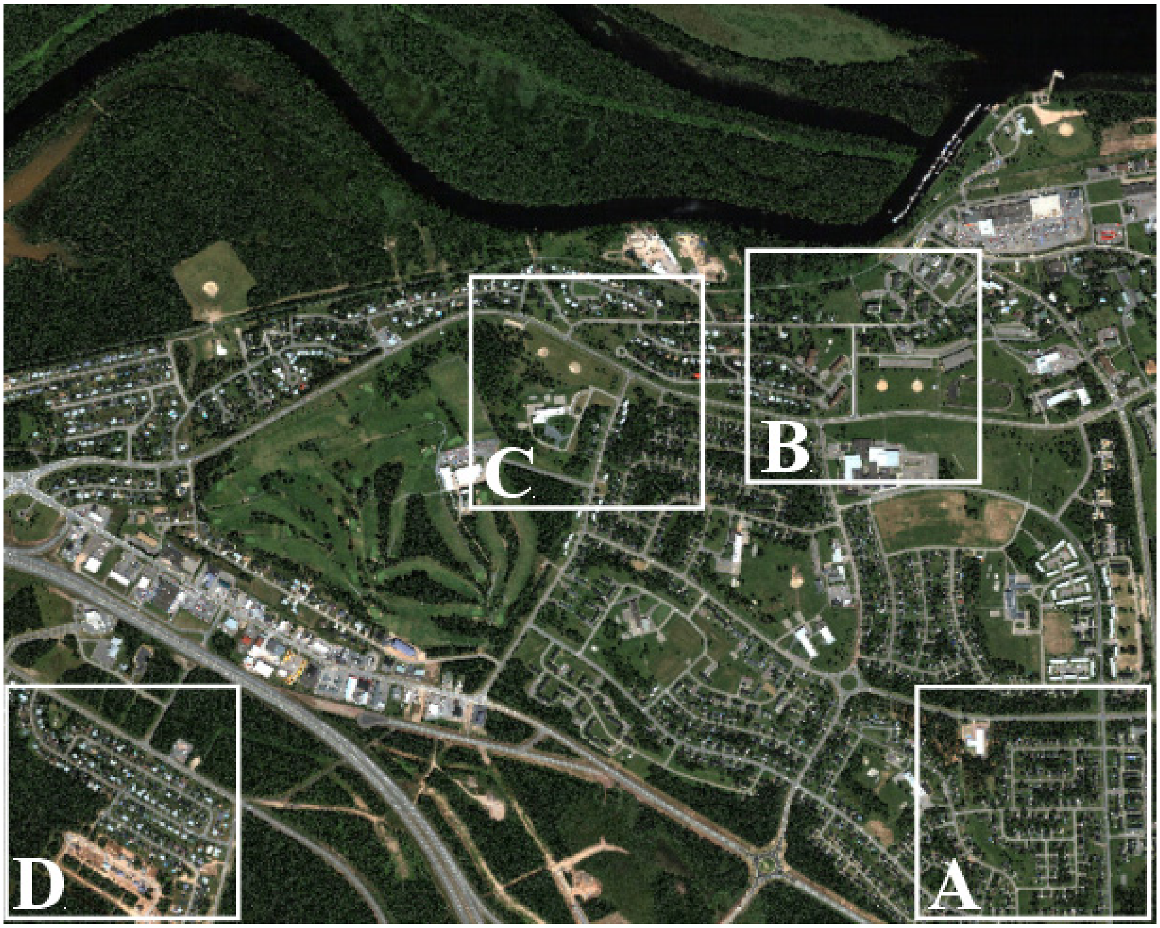


Figure 2.7
Test areas for segmentation parameter selection tool

2.6 Software

Definiens Imaging GmbH released its eCognition software in fall 2000. This application employs an object-oriented approach for the classification of land cover. eCognition accomplishes this by using a “Region-Merging” technique [Darwish et al., 2003; Carleer et al., 2004] called “Fractal Net Evolution” to extract image object-primitives in varying resolutions [Baatz and Schape, 1999]. Classification of meaningful image object-primitives instead of pixels separates eCognition from most other commercial classification approaches. Through multiresolution segmentation followed by the application of a fuzzy rule base for classification, eCognition has been designed to overcome the challenges associated with the classification of textured data that is characteristic of modern VHR sensors. The specifics of object-oriented classification, the Fractal Net Evolution Approach (FNEA), and its realization in eCognition will be covered in detail in Chapter 3. This research will use eCognition version 4.0 for the object-oriented land cover classification task.

2.7 Constraints and Limitations

The limitations encountered in the conduct of this project were not considered to be of a serious nature nor did they compromise the research at any point. They are worthy of note, however, and will be discussed in this section.

Availability of the data was the first limitation. The QuickBird data was acquired over and around the Canadian Forces Base Gagetown military training ranges. Consequently, a large selection of rural data was gathered but very limited urban data was available. Arguably, the application of object-oriented classification and the proposed fuzzy tool offer the largest advantage in the complex urban environment. Therefore, other urban images would have assisted in the development, evaluation and testing phases of this research.

Size of the study areas was also limited. This was primarily due to the computational time required for eCognition to perform the lowest level segmentation (starting from individual pixels). This process often took on the order of several minutes to complete corresponding to the size of the input images. Since it was necessary to repeat these processes several times in the course of the research, the time factor was substantial. Therefore, any images of larger size would have been impractical for this research application.

Finally, eCognition Professional was granted to UNB under a six month research license. This was enough time to permit completion of classification accuracy assessment for the test data sets. After the license expired, however, further classification testing was limited. This included limiting evaluation of the fuzzy tool through measured improvement on classification accuracy.

Chapter 3

Object-Oriented Classification

> *The classification of an entity relies upon the context within which it is embedded. Establishing the context of an entity, however depends on the ability to group like entities, and therefore requires some form of classification. The latter is the segmentation problem.*
>
> [Flack, 1996; de Kok et al., 2000]

The aim of this chapter is to outline the general theory of object-oriented classification and the specific details of how it is realized in eCognition. Starting with the image segmentation problem, the approaches used to extract image objects from remotely sensed imagery will be discussed in general terms. This will be followed by a detailed discussion of eCognition's implementation of the FNEA. The chapter will then move to a discussion on object classification and conclude with an overview of fuzzy classification in eCognition.

3.1 Image Segmentation

Classification of meaningful image objects, instead of pixels, separates object-oriented classification from most other classification approaches. The grouping of pixels together to form image objects is carried out in the preliminary segmentation stage. The result from the segmentation process is an image divided into a number of contiguous regions that serve as “building blocks and information carriers for subsequent classification” [Definiens Imaging GmbH, 2004b].

3.1.1 Image Objects and Image Object Primitives

As the user selected segmentation parameters vary, the resulting objects will change. After each segmentation is complete, it remains the user’s responsibility to determine what the resulting objects represent. When working with a new data set, it is common for the initial extracted objects to have very little meaning. For example, an object representing a patch of grass in a large grass sports field has little significance. These objects are more aptly called object primitives. Therefore, a distinction is made between objects and object primitives. The goal of segmentation in a subsequent step should be merge object primitives together into meaningful image objects. In our example, a meaningful object would be one object that represents the entire sports field. In this way, we can take advantage of the spectral and spatial properties of the object in the classification stage.

It is impractical to expect that all objects will exactly represent the land cover objects as perceived by the user (image objects). Although it should be the goal of the user to extract these objects from the imagery, a realistic expectation is the extraction of object primitives that are as meaningful as possible. In this thesis, we will refer to all objects as image objects with the understanding that meaningful image object primitives are the practical realization of this goal. In other words, the extracted objects may not exactly represent the actual land cover objects as perceived by the user, but are as close as possible using the segmentation routine and will therefore be referred to as image objects.

3.1.2 General Approaches to Segmentation

"Segmentation of non-trivial images is one of the most difficult tasks in image processing" and remains the focus of significant research [Gonzalez and Woods, 2002]. As mentioned in Section 2.2, segmentation approaches can be classed as either boundary-based or region-based [Gonzalez and Woods, 1992; Janssen et Molenaar, 1995; Zhang, 1997; Carleer et al., 2004]. The different techniques within each category are too numerous to cover in any degree of detail nor is it required since very few are robust enough to be useful in an operational environment [Definiens Imaging GmbH, 2004b]. However, the general concept of each approach along with some of the more prominent techniques will be discussed during the remainder of this section.

3.1.2.1 Boundary-Based Approach

Boundary-based algorithms rely on discontinuity detection techniques to extract the structure of image objects. One of the simplest methods to accomplish this task in the spatial domain is the use of a spatial mask for edge detection. Employing a first order derivative approach, the Prewitt and Sobel operators are among the most popular but suffer from their sensitivity to noise within the image [Gonzalez and Woods, 2002]. The second order derivative, implemented through the Laplacian mask is even more sensitive to noise and for this reason it is often implemented after a smoothing filter. Once edge detection is complete, the image must be post-processed to close the pertinent objects while reducing the edge effects due to noise and other spurious results which often appear in highly textured data [Gonzalez and Woods, 2002]. For this reason, discontinuity based techniques are less than ideal for VHR satellite imagery with a characteristically high spectral variance.

3.1.2.2 Region-Based Approach

Region-based algorithms associate pixels with similar characteristics into contiguous regions [Zhang, 1997; Carleer et al., 2004]. Thresholding remains one of the most straightforward region-based segmentation techniques. In its simplest form, a threshold (i.e. gray value) is selected based on trial and error or through an analysis of the image histogram by the user or specified algorithm. Examining the entire image histogram to determine the threshold is a global operation that aims to separate regions based solely on gray level. In a more sophisticated form, thresholding can be performed by taking into consideration local properties (local thresholding) and pixel locations within the image (adaptive thresholding) [Gonzalez and Woods, 2002]. Although these techniques are relatively easy to implement and can be applied to multispectral imagery, more sophisticated techniques such as region growing and region merging offer further promise in terms of their robustness and applicability across a variety of data sets.

Region growing refers to a procedure that starts with a number of "seed" points and through the definition of similarity criteria, regions are formed by grouping similar pixels to the associated "seeds" [Gonzalez and Woods, 2002]. Region merging works in a similar fashion, but focuses on merging groups of pixels that have been previously created by some method [Gonzalez and Woods, 2002]. If you consider single pixels as the regions from which to start, the two methods cannot be distinguished. This is the case that we will focus on.

In the most general case, *n* regions extracted from the image *R* through a region merging routine must satisfy the following criteria [Gonzalez and Woods, 2002]:

a. $\bigcup_{i=1}^{n} R_i = R$.

b. R_i is a connected region, where $i = 1,2,\ldots,n$.

c. $R_i \cap R_j = \varnothing$ for all *i* and *j*, $i \neq j$.

d. $P(R_i)$ = TRUE for $i = 1,2,\ldots,n$, where $P(R_i)$ is a logical predicate.

e. $P(R_i \cup R_j)$ = FALSE for any adjacent regions R_i and R_j.

In this instance, a connected region refers to a region whose pixels are, according to some definition, related as neighbors. In addition, the predicate $P(R_k)$ is the condition that is applied to all the pixels that comprise the region R_k. For a region merging routine, this predicate is normally a condition of similarity in some sense.

Starting at the pixel level with single pixel regions and merging these regions to form meaningful image objects requires the definition of a stopping criteria [Baatz and Schape, 2000; Gonzalez and Woods, 2002]. Problems arise when the stopping rule relies solely on local characteristics of the objects and do not take the region merging history into account. To overcome this shortfall, additional criteria that consider size and shape of the resulting objects add considerable effectiveness to this approach, but rely on some degree of a priori knowledge of the objects of interest [Gonzalez and Woods, 2002]. The region-based approach to segmentation is used in eCognition.

3.1.3 Region Merging in eCognition

Combining the "fractal structure of the world and of semantics with object orientation", Definiens Imaging designed and implemented a region merging approach to segmentation called 'Fractal Net Evolution' [Baatz and Schape, 1999]. This technique was designed with the view to meeting six aims including the [Baatz and Schape, 2000]:

a. Production of homogeneous image object-primitives;

b. Adaptability to different scales;

c. Production of similar segment sizes for a chosen scale;

d. Applicability to a variety of data sets;

e. Reproducibility of segmentation results; and

f. Requirement for reasonably fast performance.

The first three are the most important for our discussion and will be discussed in further detail during the remainder of this section.

3.1.3.1 Defining the Similarity Condition

Using the basic concept of region merging, accomplishment of the first aim outlined above, required the establishment of a logical predicate condition to evaluate whether or not to merge two adjacent image objects. The resulting condition was a definition of the degree of fitting between two objects based on homogeneity criteria.

To determine the degree of fitting, eCognition focuses on two distinct features: (1) spectral heterogeneity change, $h_{spectral}$, and (2) shape heterogeneity change, h_{shape}. [Baatz and Schape, 2000; Definiens Imaging GmbH, 2004b]. The overall spectral heterogeneity change, $h_{spectral}$, is a measure of the object heterogeneity difference (similarity in feature space) resulting from the potential merge of two adjacent objects (*obj*1 and *obj*2) and is given by [Definiens Imaging GmbH, 2004b]:

$$h_{spectral} = \sum_{c} w_c \left(n_{Obj1+Obj2} \cdot \sigma_c^{Obj1+Obj2} - \left(n_{Obj1} \cdot \sigma_c^{Obj1} + n_{Obj2} \cdot \sigma_c^{Obj2} \right) \right) \tag{3.1}$$

where c represents the different raster layers, w_c are the weights associated with each layer, n is the number of pixels comprising the objects, and σ_c is the standard deviation of pixel values within each layer. On the other hand, the overall shape heterogeneity change, h_{shape}, is the weighted average of compactness heterogeneity change, $h_{compact}$, and smoothness heterogeneity change, h_{smooth}, as given by [Definiens Imaging GmbH, 2004b]:

$$h_{shape} = w_{compact} \cdot h_{compact} + (1 - w_{compact}) \cdot h_{smooth} \tag{3.2}$$

where $w_{compact}$ is the weight associated with the compactness heterogeneity change. Conceptually, the most compact form describes a circle while the most smooth form describes a rectangle. Compactness heterogeneity change, $h_{compact}$, is defined as

[Definiens Imaging GmbH, 2004b]:

$$h_{compact} = n_{Obj1+Obj2} \cdot \frac{l_{Obj1+Obj2}}{\sqrt{n_{Obj1+Obj2}}} - \left(n_{Obj1} \cdot \frac{l_{Obj1}}{\sqrt{n_{Obj1}}} + n_{Obj2} \cdot \frac{l_{Obj2}}{\sqrt{n_{Obj2}}} \right) \tag{3.3}$$

where n is the number of pixels comprising the objects and l is the perimeter of the objects. Smoothness heterogeneity change is defined as [Definiens Imaging GmbH, 2004b]:

$$h_{smooth} = n_{Obj1+Obj2} \cdot \frac{l_{Obj1+Obj2}}{b_{Obj1+Obj2}} - \left(n_{Obj1} \cdot \frac{l_{Obj1}}{b_{Obj1}} + n_{Obj2} \cdot \frac{l_{Obj2}}{b_{Obj2}} \right) \tag{3.4}$$

where n is the number of pixels comprising the objects, l is the perimeter of the objects, and b is the perimeter of the object's bounding box.

Together, $h_{spectral}$ and h_{shape} quantities evaluate to a single value that is indicative of the overall heterogeneity change for the potential merge of two objects. This overall value is the so-called 'fusion' value. The fusion value, f, for the potential merge between two objects is given by [Definiens Imaging GmbH, 2004b]:

$$f = w \cdot h_{spectral} + (1 - w) \cdot h_{shape} \tag{3.5}$$

where w is the user assigned weight associated with spectral heterogeneity change. The merge between two objects will be considered if the fusion value falls below the square of a user specified threshold referred to as the "scale parameter". The relationships between these quantities are graphically represented in Figure 3.1.

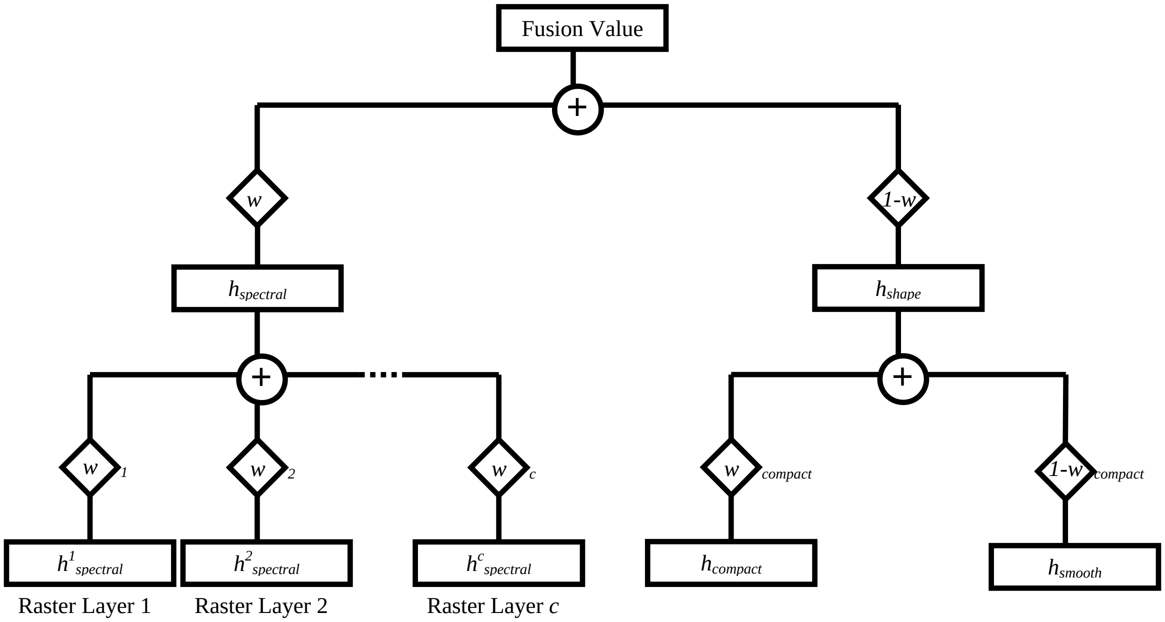


Figure 3.1
Composition of the fusion value criterion

In the context of this calculation, it is the user's responsibility to select all of the weighting elements and the scale factor. Ultimately the weights determine the heterogeneity change and the scale factor is compared to the fusion value to establish the stopping criteria. The sums of the weights are always normalized such that their sum is one. In this way, the sums of the weighted heterogeneity change quantities provide the weighted average in each case.

3.1.3.2 Optimization

The above discussion outlines how the region merging similarity condition is met through the fusion value and the scale parameter. There is further requirement, however, to provide a decision mechanism in the event that more than one object satisfies the similarity condition. For example, take the case of four objects as shown in Figure 3.2. If we start with Object A, and determine that both Object B and Object D meet the similarity criteria, we must have a method to determine which merge is the optimal choice.

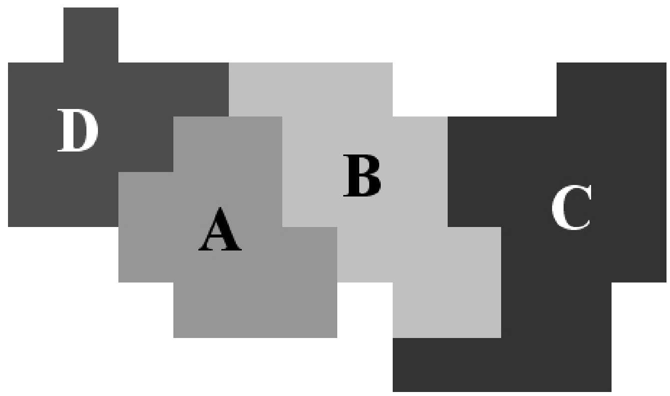


Figure 3.2
Optimization of object merging

In eCognition, this problem is addressed through an optimization procedure that aims to minimize the overall heterogeneity change. In our example, the merge of Object A and B provides the minimum change. At this point, the optimization routine looks to Object B as the starting point and determines which object merge provides the minimal heterogeneity change. If Object A is identified as the optimal choice, the merge proceeds since the two objects are mutually the best choice. If another object, for example Object C, is the optimal choice for the merge with Object B, then the optimization routine looks to Object C as the starting point to find the object that provides the minimal heterogeneity change. The process continues in this fashion, following the gradient of homogeneity within the image until mutually best fitting objects can be found [Baatz and Schape, 2000].

3.1.3.3 Scale, Size, and the Stopping Criterion

The scale parameter is an adjustable quantity designed to meet the second segmentation aim outlined in Section 3.1.3. Recall that scale in this context refers to the degree of object abstraction. As a result, the scale parameter in eCognition is simply a threshold value limiting the degree of object abstraction by monitoring the degree of heterogeneity change as objects iteratively merge. Consequently, as the scale parameter increases the region merging algorithm will permit more merges and the regions grow larger. While scale refers to the degree of object abstraction, size refers to the actual physical dimension of the object. Therefore, in eCognition there is a distinct difference between scale and size, although they are closely related in the context of this procedure. The stopping criterion is met when there are no longer any merges that satisfy the threshold established by scale parameter.

By employing an evenly distributed treatment order over the entire image, regions grow at a similar rate across the image. More homogenous regions will tend to grow larger as would be expected from our definition of heterogeneity as discussed above. In general, however, the regions can be described as similar in size for any user-defined scale, achieving the third segmentation aim in Section 3.1.3.

3.2 Fuzzy Classification

Employing the object-oriented approach, eCognition is able to take advantage of a diverse array of features for classification based on tone, texture, size, shape, and context [Definiens Imaging GmbH, 2004a]. eCognition employs these features in a classification scheme based on fuzzy logic, which provides the user with a powerful tool to manage the inherent complexities that arise using the object-based approach. While a detailed theoretical discussion of fuzzy logic will be presented in Chapter 5, the remainder of this chapter will focus on the general concepts by which fuzzy classification is carried out in eCognition.

3.2.1 Membership Functions

Each class in the classification hierarchy is described by one or more fuzzy sets. Fuzzy sets are built using features and user-defined membership functions. In this way, membership functions map feature values to the interval 0 to 1. For example, the class 'water' can be described by an object's low mean value in the near infrared (NIR) band. We will make the assumption that this class can be defined sufficiently using only this one condition. Therefore, to define this class we must define a membership function to describe the fuzzy set *Low_NIR* such that *Low_NIR*: *Mean_NIR_Band* → [0,1]. Since this is the only condition, the following rule can be formulated:

$$\mu_{water}(\text{object}) = \mu_{Low\_NIR}(Mean\_NIR\_Band(\text{object})) \qquad (3.6)$$

where each object will be assigned a membership value to the class 'water' that is equal to the membership of the object to the fuzzy set *Low_NIR* through the feature *Mean_NIR_Band*.

In the case where more complex class descriptions are required, membership functions can be combined through fuzzy operators. Let us assume that a lake can be described as being composed of water and having a very compact shape. Combining the conditions we can create a rule to describe membership to the class 'lake' according to:

$$\mu_{lake}(\text{object})=[\mu_{Low\_NIR}(\mathit{Mean\_NIR\_Band}(\text{object})) \cap \mu_{Compact}(\mathit{Compactness}(\text{object}))] \quad (3.7)$$

where the membership to the class 'lake' is the minimum of the object's membership to fuzzy set *Low_NIR* and fuzzy set *Compact*.

Since the class descriptions (rules) are organized within a classification hierarchy, complex rules can be simplified. Using results from classification on a previous level of the hierarchy, such as the classification of class 'water', we can proceed to use this result for the classification of class 'lake'. Through this approach, equation (3.7) becomes:

$$\mu_{lake}(\text{object})=[\mu_{water}(\text{object}) \cap \mu_{Compact}(\mathit{Compactness}(\text{object}))]. \qquad (3.8)$$

This simplifies the situation considerably, and the result is a hierarchical classification knowledge base.

This fuzzy methodology permits objects to partially belong to any class. In the end, however, the defuzzification process evaluates the highest membership value for a particular object and assigns the object to the appropriate class. In other words, the result is a classification of each object as we would expect from any other conventional form of classification with each object assigned to a land cover type, the only difference being that an object may have partial membership to other classes as well.

3.2.2 Nearest Neighbor Functions

For very complicated class descriptions requiring the use of numerous object features, the membership function approach does not work well and can be handled much better using a nearest neighbor approach in multidimensional feature space [Definiens Imaging GmbH, 2004b]. Nearest neighbor works in a similar manner to the minimum distance supervised classification technique which is common to the pixel-based approach. The overall implementation is simplified using the case of a segmented image since training areas are simply the objects themselves, each object containing a number of representative pixels. Once the samples have been identified, all remaining objects in the image are assigned the same class as the closest training object in feature space.

Lillesand and Keifer [1994] note that the minimum distance classifier is generally not used on data with high variance due to problems separating the classes in multispectral space. Using objects, however, there are two distinct advantages over the minimum distance classifier as conventionally applied to pixels in multispectral space: (1) high multispectral variability is managed well through the use of image objects, and (2) features available to the user through the use of objects instead of pixels promises better overall separation in feature space than in multispectral space.

Since eCognition is based on a fuzzy classification scheme, the nearest neighbor classifier must also associate a fuzzy membership value to each class in the hierarchy. To accomplish this, the membership value is calculated as a function of distance in feature space between the object being classified and the nearest training object for each class. Therefore, in the context of the resulting classification knowledge base it does not matter which technique is employed (nearest neighbor or membership function) since they both generate a fuzzy classification result.

Chapter 4

Implementation of Pan-Sharpened Data for Classification

Things which we see are not by themselves what we see…. It remains completely unknown to us what the objects may be by themselves and apart from the receptivity of our senses. We know nothing but our manner of perceiving them.

[Immanuel Kant]

Approaching the classification problem using the object-oriented methodology, realized through eCognition, classification can be carried out at similar object scales. This will permit a comparison as to the applicability of original multispectral and UNB Pan-Sharpened data to the classification problem. In addition to permitting a reliable comparison, the object-oriented methodology has the potential to provide better overall classification results than other pixel-based methods since this approach is a seemingly better suited alternative for modern VHR sensors and textured data. This chapter will outline the classification process as applied to our data set comprised of the original and pan-sharpened suburban and rural QuickBird images (see Chapter 2), show results, and identify problems encountered in this implementation. The accuracy analysis and results comparison will be described in Chapter 7.

4.1 Image Classification

4.1.1 Stage 1 - Segmentation

Segmentation of imagery into meaningful image objects is essential to classification success. Given the number of user-defined parameters to accomplish this task in eCognition, segmentation is likely the most difficult and time-consuming process in the object-oriented classification workflow. Throughout the remainder of this section, we will describe the segmentation of our data set and the reasoning behind our selection of parameters.

4.1.1.1 Spectral Band Selection and Weighting

The first step in segmentation involves the selection of weights, w_c, that correspond to each raster layer, c, in the input data set. For the QuickBird imagery used in this research, each of the five bands (panchromatic, blue, green, red, and near-infrared) must be assigned an appropriate weight in an effort to successfully segment the image into meaningful image objects. Two problems arise in this task. First, the pan-sharpened data set already has the information of the panchromatic channel incorporated into the multispectral bands through the fusion process. On the other hand, the original multispectral data does not contain this information. Inclusion of the panchromatic channel as a separate input layer into the segmentation process, therefore, would seem somewhat redundant for the pan-sharpened data but would seem necessary for the original multispectral data. The second problem concerns the issue of weighting factors other than zero (excluded from the segmentation process) or one (included in the segmentation routine). Once the user decides which layers to use, increased or reduced weights can be assigned to certain layers in an effort to improve the overall segmentation results. The appropriate selection of these weights, however, is not a straightforward task. Incorrect selection of the input bands and inappropriate weights can result in poor objects and consequently an unsatisfactory classification [Wong et al., 2003].

To address the first problem and to examine the benefit offered by the panchromatic image channel for each scene (rural and suburban), two segmentations were carried out on the original imagery and two segmentations were performed on the pan-sharpened imagery. The first segmentation excluded the panchromatic layer and focused solely on the information contained in the multispectral bands. The second segmentation in each case was performed using both the panchromatic and multispectral image layers. This approach resulted in four segmentations (designated A through D) for each image scene (Table 4.1).

Table 4.1
Data set composition for scene segmentation

Segmentation		A	B	C	D
Data					
Pan-Sharpened Multispectral	Blue	X	X		
	Green	X	X		
	Red	X	X		
	Near Infrared	X	X		
Panchromatic	Panchromatic		X		X
Original Multispectral	Blue			X	X
	Green			X	X
	Red			X	X
	Near Infrared			X	X

The second problem identified above regarding the weights associated with the different channels is not so simple to evaluate. In this case, it is up to the user to specify the weights according to experience and results achieved through trial and error segmentation. Unfortunately, trial and error by nature is very time-consuming and the difficulty selecting the appropriate raster layer weights along with all of the other user specified parameters (see Figure 3.1) quickly becomes an overwhelming task. The user could easily spend many hours trying different combinations, but realistically, only a small number of combinations at each segmentation level are tried before the user is forced to accept the segmentation and move to the classification stage.

In this research, all the layers were given equal weighting for segmentation of the rural imagery. This simple approach appeared to work reasonably well given the relative simplicity of the rural data set. In the case of the suburban data set, layer weights were modified by trial and error in an attempt to improve the overall segmentation owing to the complexity of the imagery. The difficulty encountered in the segmentation of urban areas was identified by Hofmann [2001] and in a large part attributed to the spectral similarity of the different bands in VHR sensors. Hence, specific weights for the different suburban image channels were used to achieve a reasonable segmentation.

In both rural and suburban cases, segmentation was carried out using a bottom-up approach [Hofmann, 2001]. Therefore, starting at the lowest level (smallest objects), four levels of image objects were created with each level containing objects larger than the level previous. The selection of four object levels was determined somewhat arbitrarily ensuring that sufficient levels were created to adequately represent all of the different land cover types to be classified. In the absence of any scaling rules or specific guidance in this regard, this seemed a reasonable deduction. Since the object sizes were different at each level, it permitted land cover classification at the most appropriate level, while allowing refinement and extraction of other objects at smaller scales. The raster layer weights for these four levels of segmentation are shown in Tables 4.2 through 4.5.

Table 4.2
Layer weights for rural imagery segmentation with panchromatic layer

Segmentation Level	Layer				
	Panchromatic	Blue	Green	Red	Near-IR
1	1.0	1.0	1.0	1.0	1.0
2	1.0	1.0	1.0	1.0	1.0
3	1.0	1.0	1.0	1.0	1.0
4	1.0	1.0	1.0	1.0	1.0

Table 4.3
Layer weights for rural imagery segmentation without panchromatic layer

Segmentation Level	Layer				
	Panchromatic	Blue	Green	Red	Near-IR
1	0.0	1.0	1.0	1.0	1.0
2	0.0	1.0	1.0	1.0	1.0
3	0.0	1.0	1.0	1.0	1.0
4	0.0	1.0	1.0	1.0	1.0

Table 4.4
Layer weights for suburban imagery segmentation with panchromatic layer

Segmentation Level	Layer				
	Panchromatic	Blue	Green	Red	Near-IR
1	1.0	1.0	1.0	1.0	1.0
2	1.0	1.0	1.0	1.0	2.0
3	1.0	1.0	1.0	1.0	1.0
4	1.0	0.0	0.0	0.0	1.0

Table 4.5
Layer weights for suburban imagery segmentation without panchromatic layer

Segmentation Level	Layer				
	Panchromatic	Blue	Green	Red	Near-IR
1	0.0	1.0	1.0	1.0	1.0
2	0.0	1.0	1.0	1.0	2.0
3	0.0	1.0	1.0	1.0	1.0
4	0.0	0.0	0.0	0.0	1.0

4.1.1.2 Scale, Shape, and Compactness Parameter Selection

To complete the segmentation at each of the four levels discussed above, the user must select appropriate scale, shape (versus spectral), and compactness (versus smoothness) parameters. To aid in this task, eCognition provides the following guidance [Definiens Imaging GmbH, 2004b]:

a. Scale should be as large as possible but small enough to ensure separation of different land cover classes. In this way, objects are abstracted as much as possible without growing so large as to join with other land cover regions.

b. Spectral properties should be weighted as high as possible while the shape parameter should be weighted only as high as necessary.

c. The importance given to compactness depends on the properties of the objects of interest in the imagery.

These rules are useful but suffer from their generality. This creates difficulty in the selection of appropriate segmentation parameters that will ultimately lead to a convincing segmentation. This difficulty was highlighted by Schiewe et al [2001].

> Considering the transparency of the software in use it has to be stated that with increasing complexity the control and understanding significantly decrease. For instance, the effects of the abstract scale parameter settings can be hardly predicted. Here, the aim to combine various parameters to one number makes the initial use easier, but the actual, iterative process more difficult [Schiewe et al., 2001].

As long as the trial and error process is the approach recommended by Definiens Imaging [2004b], the iterative segmentation process will remain a difficult and time-consuming task. Nevertheless, it remains crucial to successful classification.

In the absence of a tool to guide the selection of parameters, they were selected based on trial and error until a visually pleasing result was achieved. Keeping in mind that different raster layers were used for segmentation of the same scene, shape and compactness parameters were left unchanged for equivalent hierarchy levels. In addition, since scale is a measure of object abstraction, the scale parameter was further adjusted between segmentations to ensure that the average size of the resulting objects were as close as possible. This was particularly important at the higher segmentation levels due to the disparity in textures present in the different data sets, and was a necessary step to ensure comparability between the resulting classifications. Absence of this refinement may have been possible, but the sensitivity of classification to scale is not yet predictable. Tables 4.6 and 4.7 specify the parameters chosen.

Table 4.6
Rural scene segmentation parameters

Level	Scale				Spectral	Shape	Compactness	Smoothness
	A	B	C	D				
1	15	15	15	15	0.9	0.1	0.9	0.1
2	42	43	40	39	0.8	0.2	0.8	0.2
3	82	86	80	79	0.7	0.3	0.8	0.2
4	136	145	140	141	0.7	0.3	0.8	0.2

Table 4.7
Suburban scene segmentation parameters

Level	Scale				Spectral	Shape	Compactness	Smoothness
	A	B	C	D				
1	12	12	12	12	0.9	0.1	0.9	0.1
2	30	30	34	32	0.8	0.2	0.8	0.2
3	50	51	49	48	0.6	0.4	0.8	0.2
4	200	180	197	169	0.8	0.2	0.8	0.2

4.1.1.3 Segmentation Results

Each segmentation level in the object hierarchy was created through the selection of a unique set of segmentation parameters as outlined in the previous section. The parameter that had the largest impact on the size of the resulting objects was the scale parameter. By successively increasing the scale parameter at each level, we created the different levels of abstraction in the object hierarchy. An example created using eCognition demonstrates the four object level hierarchy in Figures 4.1 through 4.4.

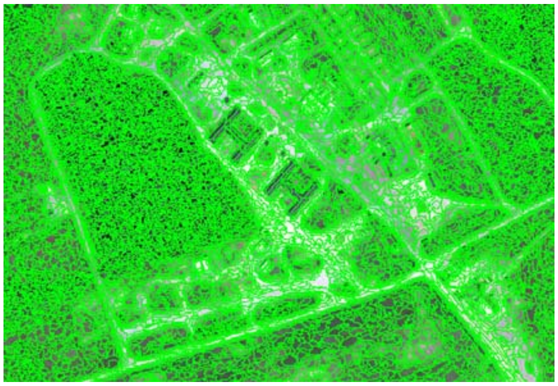


Figure 4.1
Example of segmentation at level 1

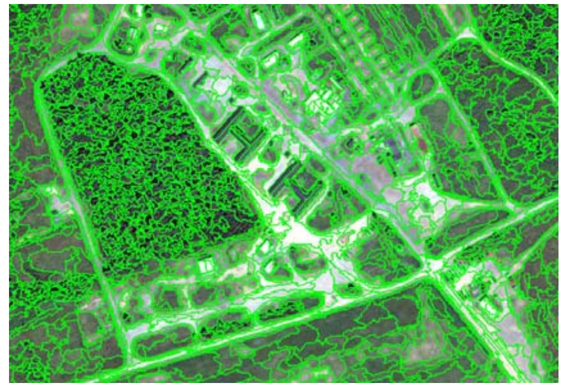


Figure 4.2
Example of segmentation at level 2

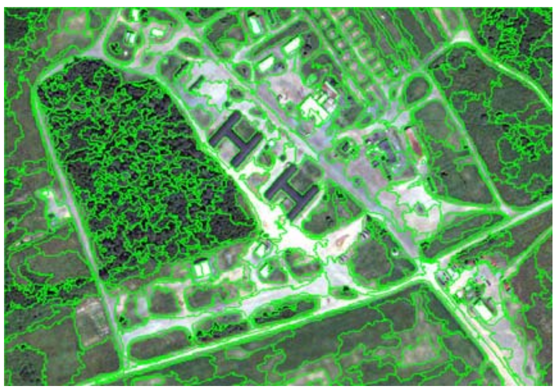


Figure 4.3
Example of segmentation at level 3

Figure 4.4
Example of segmentation at level 4

For comparison purposes, a subset of the resulting segmentations (A through D) at level 2 for the rural data set can be seen in Figures 4.5 through 4.8. It is immediately obvious that the objects in each case are different. This is what we would expect from region-merging and is not of concern so long as the each object being classified represents only one land cover class and do so in a way that is representative of the class shape. This requirement is fulfilled in the following results.

Figure 4.5
Subset of segmentation A (B, G, R, NIR layers) at level 2

Figure 4.6
Subset of segmentation B (Pan, B, G, R, NIR layers) at level 2

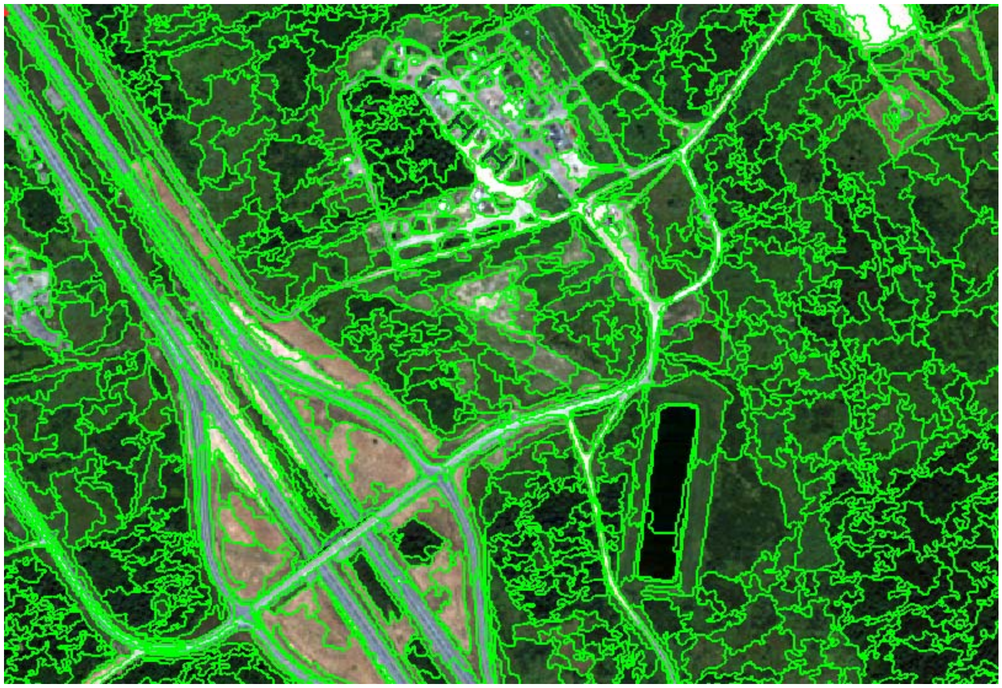


Figure 4.7
Subset of segmentation C (B, G, R, NIR layers) at level 2

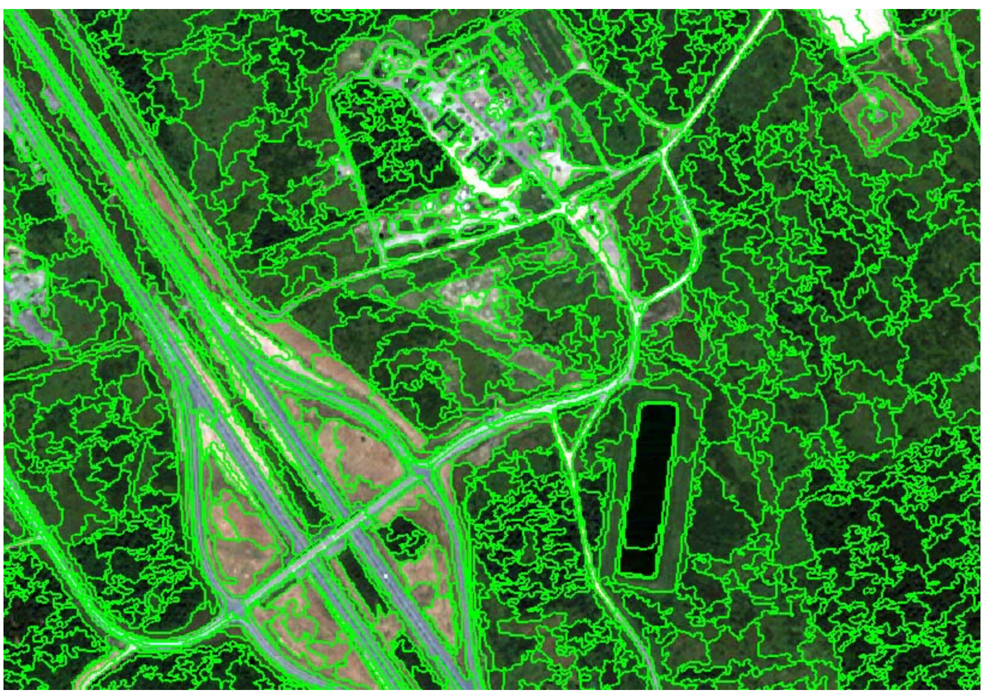


Figure 4.8
Subset of segmentation D (Pan, B, G, R, NIR layers) at level 2

The segmentation of the suburban scene demonstrates similar characteristics but is not shown here. Instead, the final classified results for both scenes will be presented in the next section.

4.1.2 Stage 2 - Classification

Once each data set has been partitioned, a classification knowledge base must be developed and used to classify the images. In eCognition this knowledge base employs both user-defined fuzzy membership function and nearest neighbor supervised classification approaches (see Section 3.2). For this project, membership function classification was the method of choice and nearest neighbor was only applied to refine certain classes as a last resort. This provided a large degree of control over the resulting classification, but at the cost of a great deal of time in the creation of the knowledge base.

4.1.2.1 Knowledge Base Development

The knowledge base was developed within eCognition using a top-down approach [Hofmann, 2001]. This approach involved classification of appropriate classes on the highest level first and refinement of the classification at each successively lower level. By following this method, land cover could be extracted at the most appropriate level and then refined. Shape, texture, and relational features were exploited as much as possible to augment spectral features and create the best classification possible. In the rural scene, vegetated and non-vegetated areas were separated on the highest level (level 4, largest objects). At this level of abstraction, some refinement was possible resulting in a number of specific non-dense vegetation classes. At the next lower level, classification results from level 4 were refined permitting trees and grass to be extracted and allowing the level 4 pavement class to be further refined into separate classes that were distinguishable in level 3 (gravel, pavement, and urban). The refinement continued in this manner to the lowest level and resulted in a total of six classes including: (1) grass, (2) gravel/soil, (3) pavement, (4) trees, (5) urban, and (6) water (Figures 4.9 through 4.12).

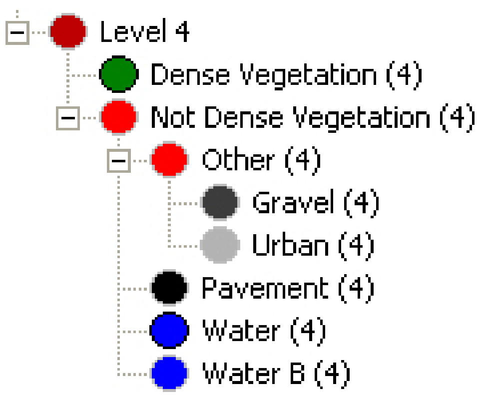


Figure 4.9
Example of classification hierarchy level 4 as developed using eCognition

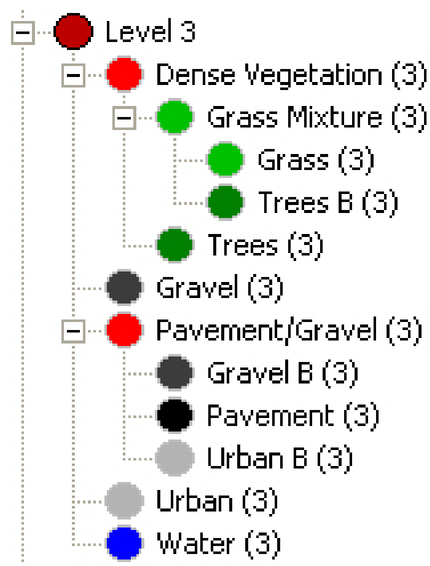


Figure 4.10
Example of classification hierarchy level 3 as developed using eCognition

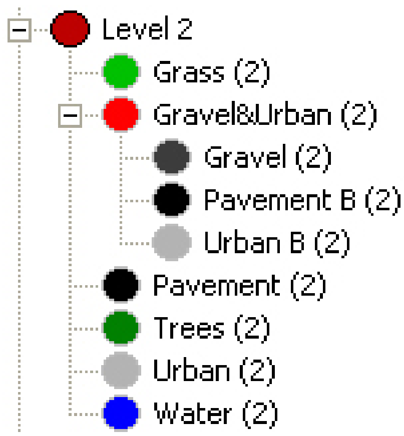


Figure 4.11
Example of classification hierarchy level 2 as developed using eCognition

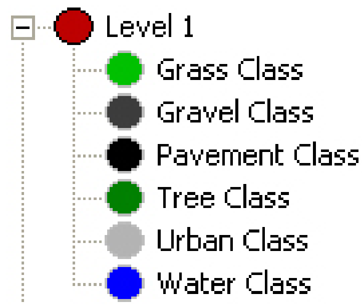


Figure 4.12
Example of classification hierarchy level 1 as developed using eCognition

For the suburban scene the same top-down method was used. In this scene a total of nine classes were extracted including: (1) deep water, (2) shallow water, (3) marsh, (4) pavement, (5) grass, (6) sparse vegetation, (7) sand/soil/gravel, (8) urban, and (9) trees.

4.1.2.2 Classification Results

Upon completion of the knowledge base for each data set, the imagery was classified using eCognition. Classification of the rural data sets (Figures 4.13 through 4.16) and suburban data sets (Figures 4.17 through 4.20) are shown below. A thorough discussion and assessment of these results are presented in Chapter 7.

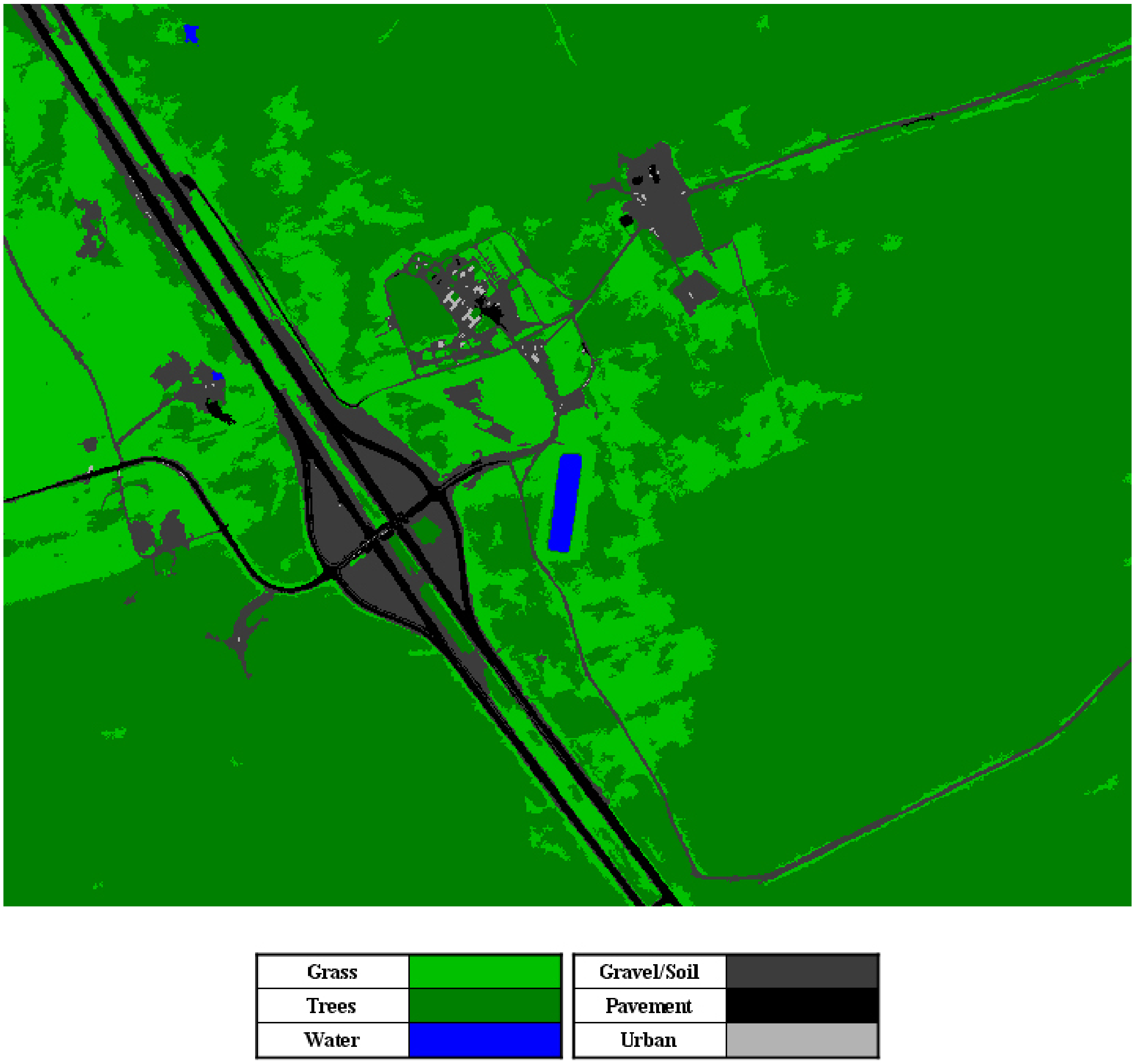


Figure 4.13
Rural scene classification using segmentation A (B, G, R, NIR layers)

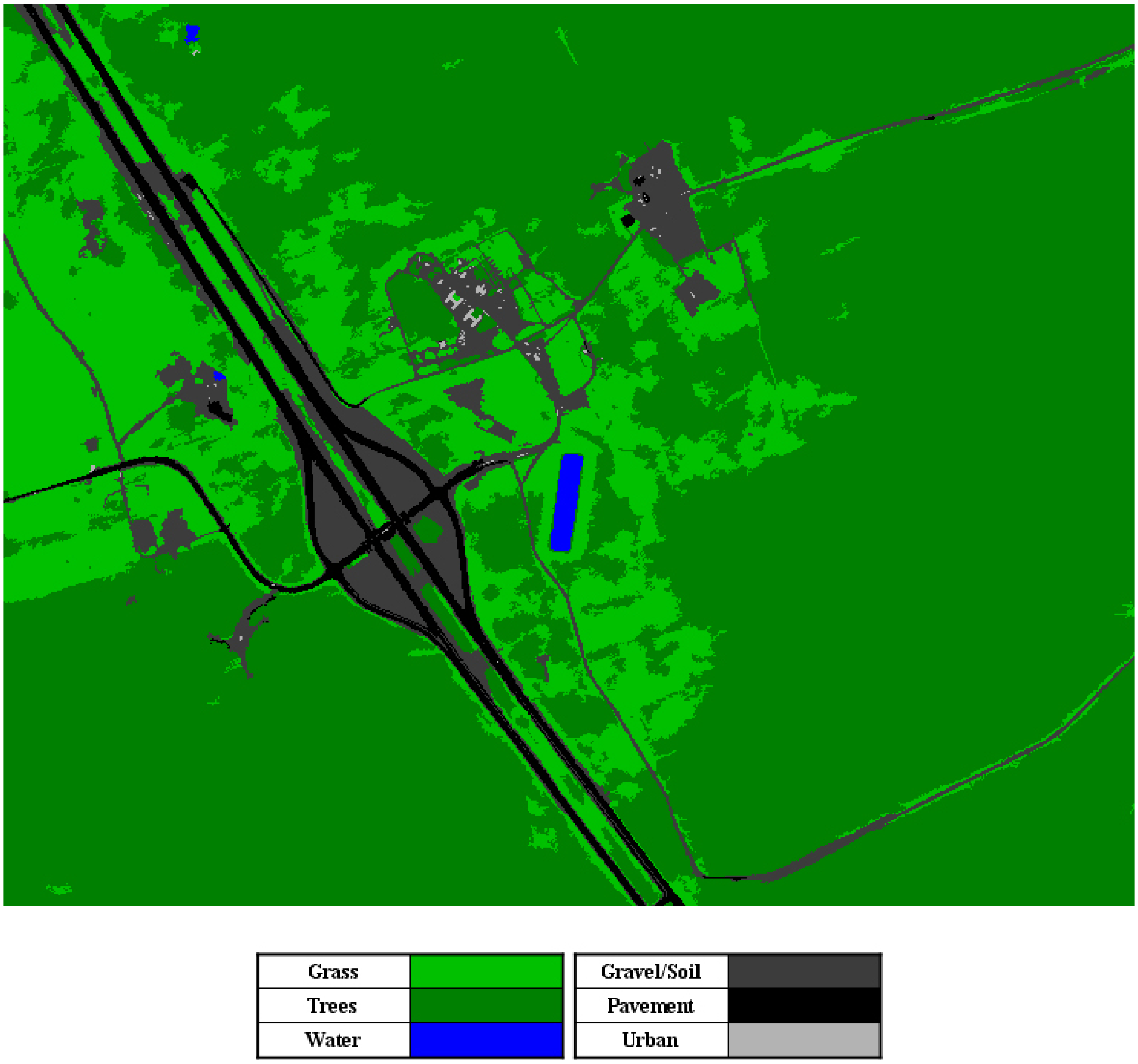


Figure 4.14
Rural scene classification using segmentation B (Pan, B, G, R, NIR layers)

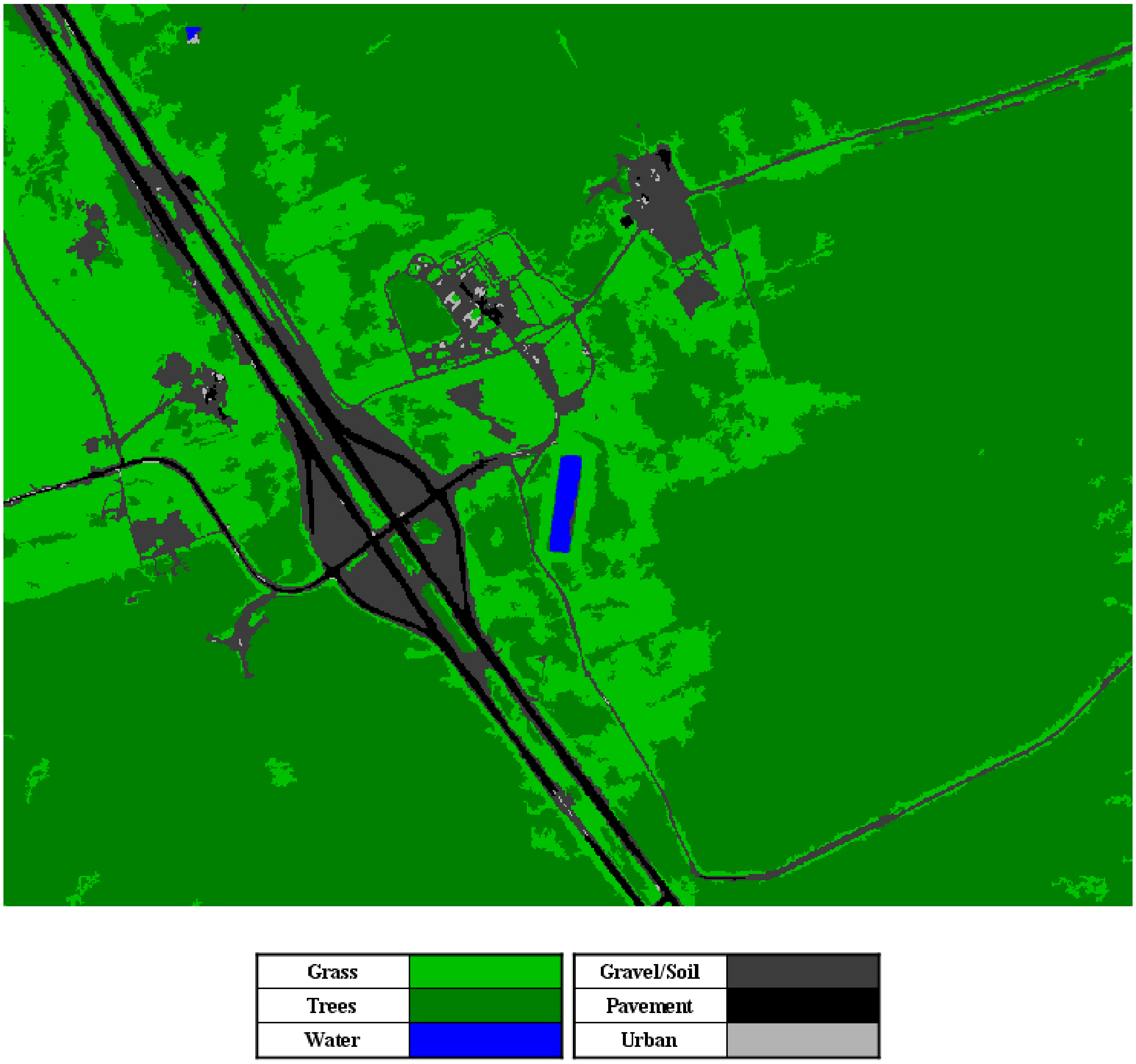


Figure 4.15
Rural scene classification using segmentation C (B, G, R, NIR layers)

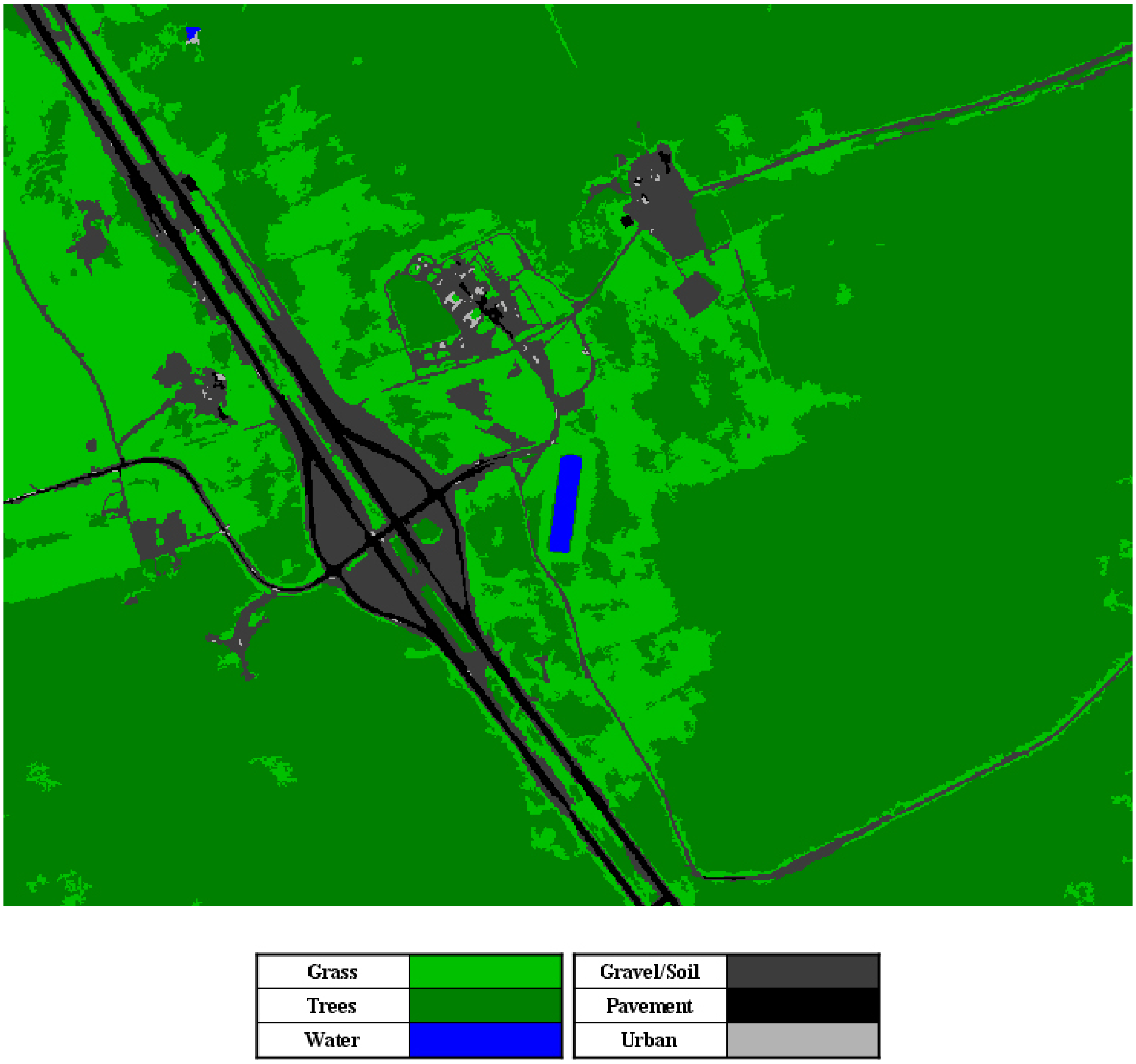


Figure 4.16
Rural scene classification using segmentation D (Pan, B, G, R, NIR layers)

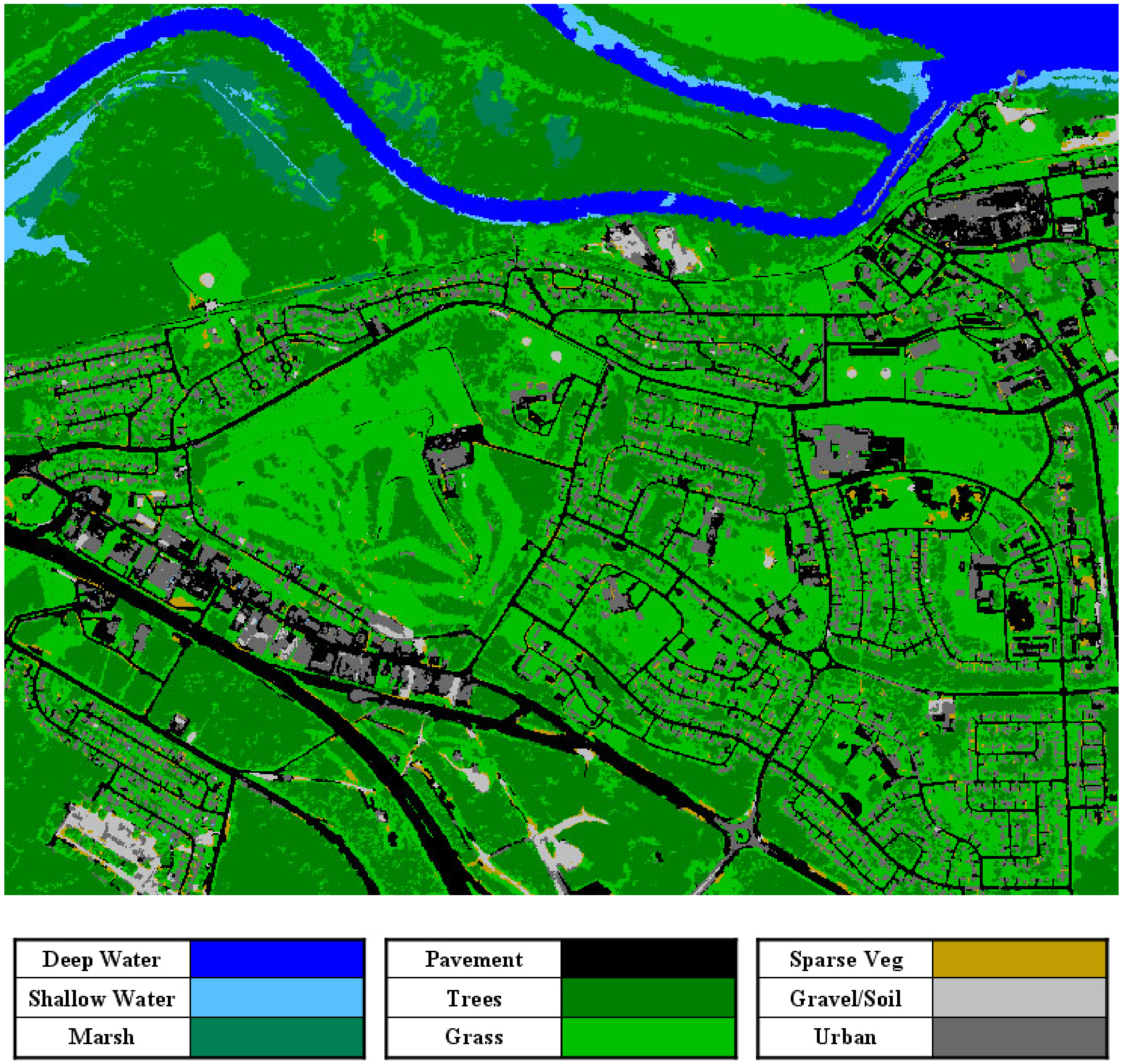


Figure 4.17
Suburban scene classification using segmentation A (B, G, R, NIR layers)

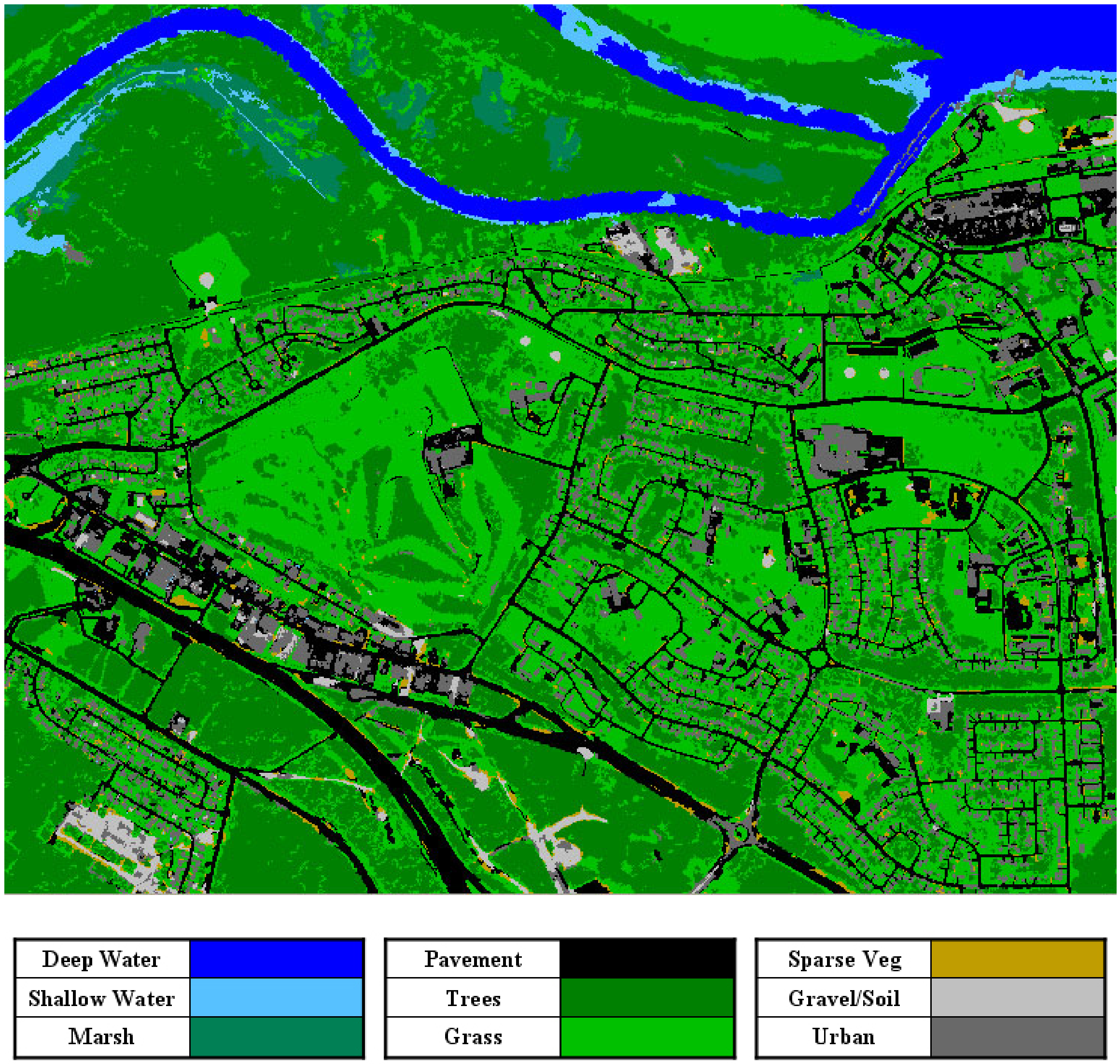


Figure 4.18
Suburban scene classification using segmentation B (Pan, B, G, R, NIR layers)

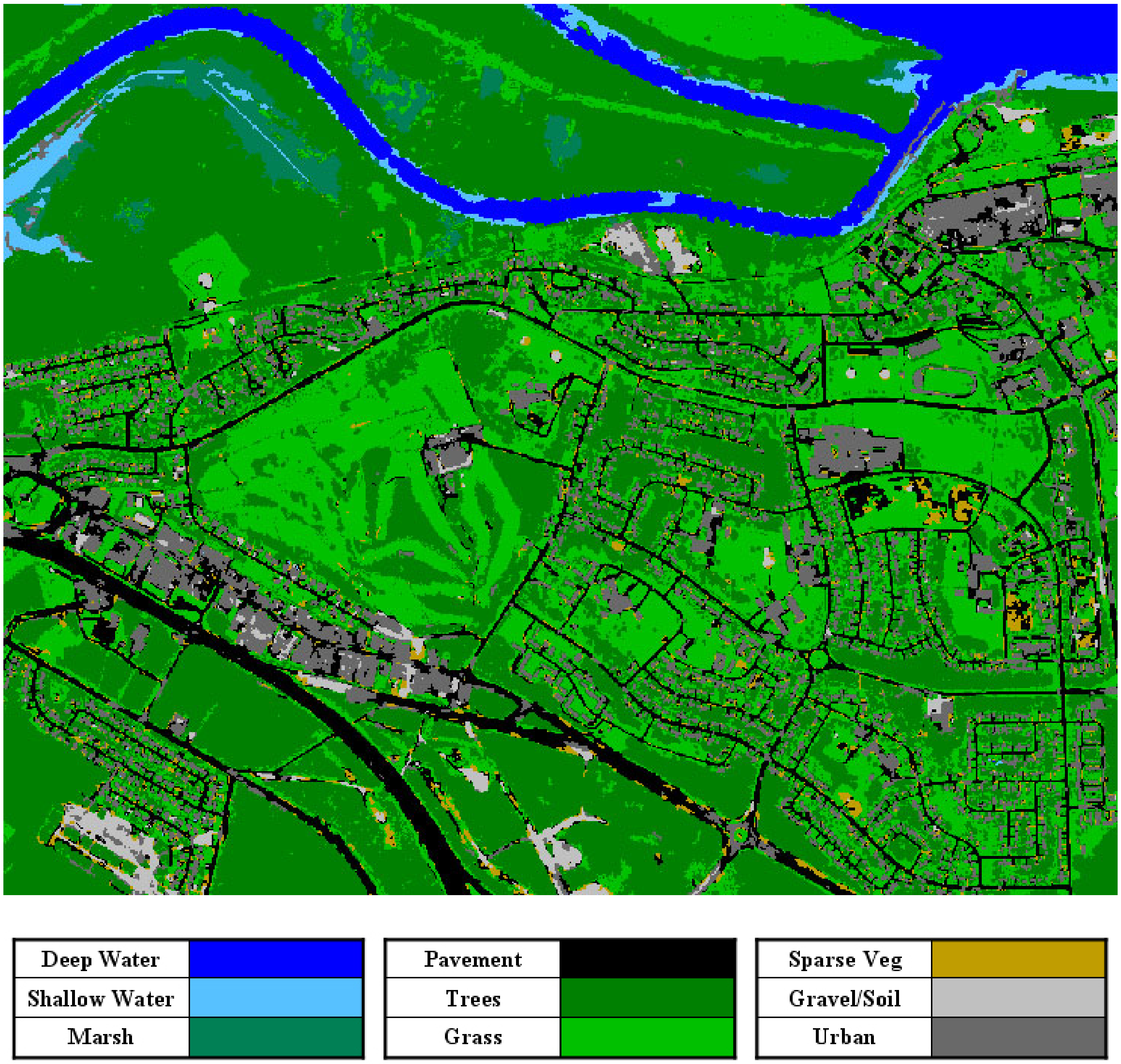


Figure 4.19
Suburban scene classification using segmentation C (B, G, R, NIR layers)

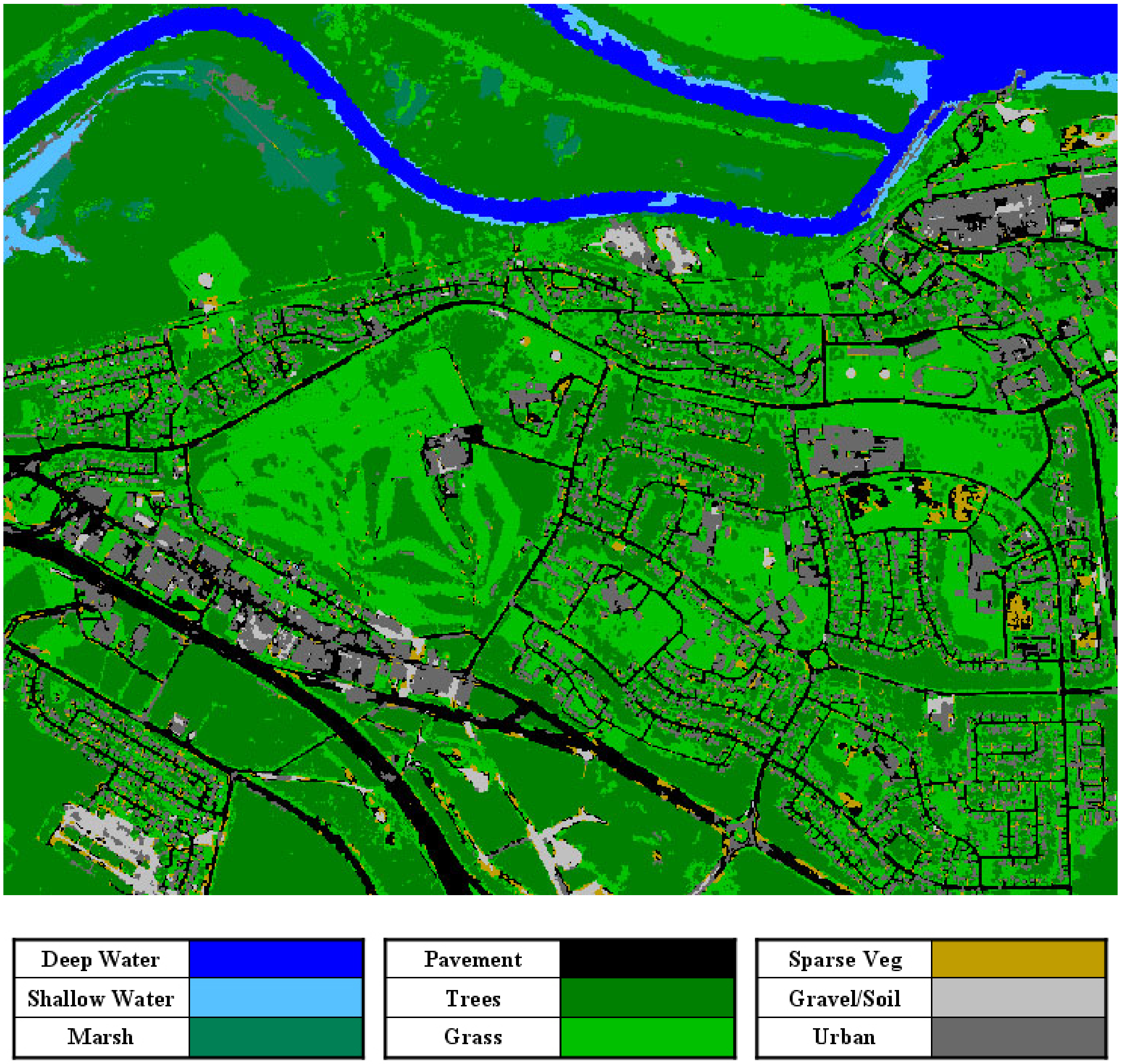


Figure 4.20
Suburban scene classification using segmentation D (Pan, B, G, R, NIR layers)

4.2 Problems Identified during Classification

Discussion in Section 4.1.1 outlined the severe segmentation difficulties encountered when implementing object-oriented classification in eCognition. The segmentation process is far from straight forward and extremely time-consuming through trial and error. Yet segmentation is the pivotal process leading to either success or failure during classification.

To date, very limited work has been completed in an effort to simplify the parameter selection process. Frauman and Wolff [2005] suggested:

> If a link can be established between the size of the objects contained in the image and the heterogeneity criterion, a user friendly rule could be derived that would allow any user to get over the time-consuming stage of finding the best segmentation before any other image analysis.

In their research, they maintained the spectral and shape criterion at a default value throughout while focusing solely on the scale parameter. This is an unrealistic simplification and does not take full advantage of these parameters. Furthermore, the discovery of a simple rule may be possible using spectral heterogeneity properties, but it becomes increasingly complex with the addition of shape descriptors. However, they concluded that a link does exist between object size and the scale parameter, but the actual rule governing this relationship remains elusive.

Therefore, the common criticism of the object-oriented image analysis is the requirement for the analyst to have significant knowledge of land cover objects of interest. The analyst must then apply this knowledge in the selection of optimal segmentation parameters with the aim of successfully extracting these objects [de Kok et al., 1999; Flanders et al., 2003; Hay et al., 2003]. Unfortunately, the user who is "aware of the spatial and spectral behaviour of the objects [and] understand[s] the underlying processing…does not always exist" [Flanders et al., 2003]. Consequently, a number of problems persist, namely: (1) determining the number of levels that should be extracted; (2) the selection of appropriate segmentation parameters for each level in a timely manner; and (3) a method of evaluation of segmentation results beyond that which is visually pleasing.

A tool designed to aid the user in this regard would prove extremely useful. Therefore, a sophisticated tool based on a fuzzy engine for parameter selection seems a logical choice. Such a tool will be proposed, developed, and implemented over the next two chapters.

Chapter 5

Fuzzy Parameter Selection

> *We say that a heap is a collection of parts…. We cannot really identify the exact number of objects that must remain in the collection in order for it to qualify as a heap, because we would probably still be willing to call it a heap, even if we removed one more item.*
>
> [Klir et al., 1997]

5.1 Introduction to Fuzzy Logic Theory

Fuzzy set theory was introduced by Lotfi A. Zadeh in 1965 to manage "uncertainty resulting from vagueness of linguistic terms in natural language" [Klir et al., 1997]. Prior to this introduction, uncertainty was dealt with using probability theory, the essence of which was prediction of future random events based on current knowledge. Although probability theory was widely accepted and used, it could not deal with all types of uncertainty and therefore was not applicable to all situations. For example, the expectation that a young person will walk into a university classroom can be described by probability theory, but the concept of 'young' is imprecise. The term 'young' cannot be described by probability theory. Consequently, Zadeh introduced the notion of fuzzy sets to provide a tool to manage uncertainty in situations involving vague natural language.

Distinguishing itself from the traditional concept of the crisp set, fuzzy set theory was able to conceptualize the idea of a set whose boundary was not sharply defined [Klir et al., 1997]. In this way members did not have to be categorized as fully included or fully excluded from a particular set. Instead, members could partially belong to a set. For the example cited above, this concept could be used to describe the extent to which a person can be considered ‘young’. The concept of partial membership introduced a new method to manage uncertainty in a simple, yet powerful manner.

Employing the concepts of fuzzy set theory, fuzzy logic lends itself particularly well to managing vague and imprecise input in a manner similar to human decision making [Kaehler, 1998]. While not initially conceived as a control system methodology, fuzzy logic performs very well in this regard and is likely the most successful area of application [Klir et al., 1997; Kaehler, 1998]. For our application, the imprecise nature of segmentation and the selection of its associated parameters make fuzzy logic seemingly well suited to this task. First, however, it is necessary to explore the realization of fuzzy control through the fuzzy inference system (FIS).

5.2 Fuzzy Inference System (FIS)

A fuzzy inference system can best be understood by breaking it down into a five step process. This process starts with the input one or more variables and through a number of sequential steps produces a definite result. The intermediate steps in this process can be generalized as [The Mathworks, 2005]:

a. Fuzzification of inputs;

b. Application of fuzzy operations in the antecedent;

c. Implication;

d. Aggregation (or inferencing); and

e. Defuzzification.

Figure 5.1 demonstrates how these steps work together to form the FIS. The concept behind each step in this process will be discussed in detail during the next few sections.

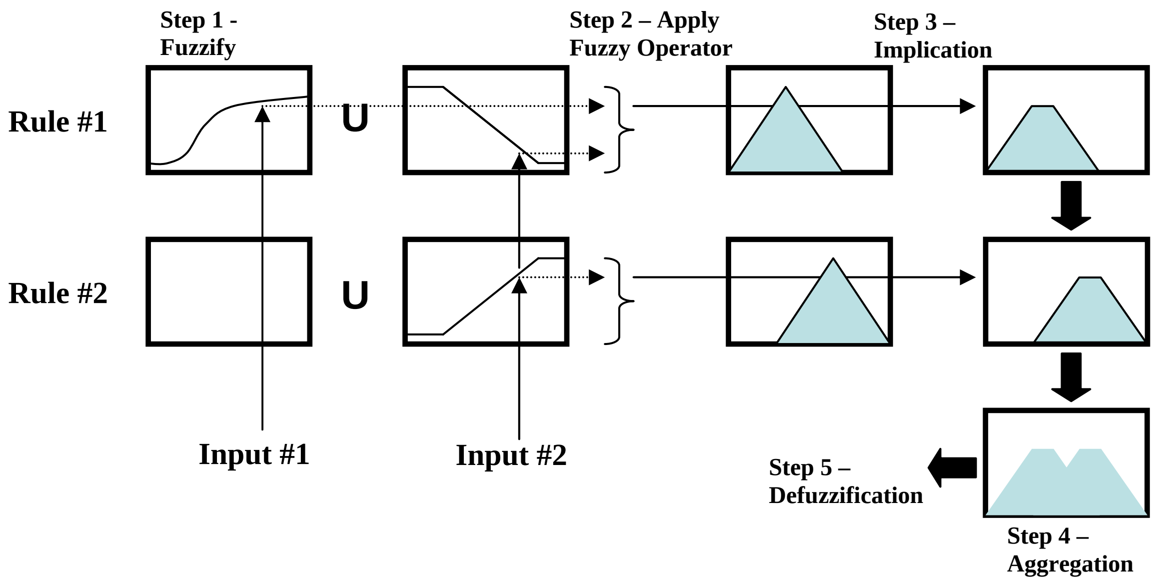


Figure 5.1
Fuzzy inference system workflow (after The Mathworks [2005, p. 2-29]).

5.2.1 Variables, Sets and Membership Functions

Any particular variable input into a system can assume a range of different values all of which come from the universal set of that variable. In other words, the universal set contains all possible values of a particular variable. This can be represented by:

$$A = \{ a \mid P(a) \} \tag{5.1}$$

where the universal set A is composed of elements a such that each element a has the property P.

To be used in a fuzzy inference system, input variables must be assigned a membership value, μ, to a fuzzy set. This process of mapping the universal set of a variable, say A, to a particular fuzzy set is carried out through a user-defined membership function B such that:

$$B : A \rightarrow [0,1]. \tag{5.2}$$

In this manner, each element $a \in A$ has an associated membership value μ to the fuzzy set B such that:

$$\mu_B = B(a). \tag{5.3}$$

This process is referred to as fuzzification and establishes the first step in the fuzzy inference system.

5.2.2 Operators

Fuzzy sets can be combined using a diverse array of fuzzy operations. This discussion will focus on the most important operations for our application. For the most part these operations are standard fuzzy operations, but where appropriate, a discussion of some non-standard operations will be covered.

5.2.2.1 Fuzzy Complement

Given the fuzzy set B from equation 5.3, the standard fuzzy complement $\overline{B}$ is the fuzzy set which expresses the degree to which *a* does not belong to fuzzy set *B* [Klir et al., 1997]. Formally, the complement is defined as:

$$\overline{B}(a) = 1 - B(a). \tag{5.4}$$

This relationship can be seen graphically depicted in Figure 5.2 by way of example. In this example, membership to fuzzy set *Inexperienced* is a function of credit hours. Using the complement operator, we can proceed to define the fuzzy set *Experienced* using equation 5.4. In this way, the fuzzy set of inexperienced students and its complement, experienced students, are both defined.

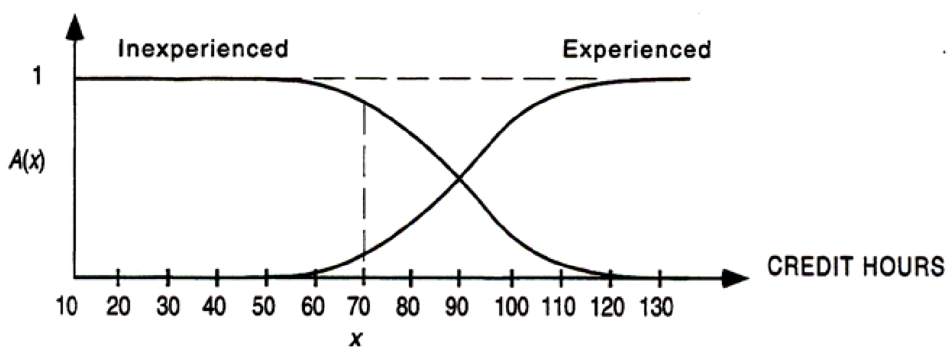


Figure 5.2
Fuzzy set of inexperienced students and its complement (from Klir et al. [1997, p. 91]).

The relationship between a fuzzy set and its complement have some specific differences from their classical set theory counterparts. One important difference to note is that a fuzzy set and its complement overlap. Therefore, an input element can have partial membership to both fuzzy sets. Given a specific number of credit hours, the input element can have partial membership to both fuzzy set *Inexperienced* and fuzzy set *Experienced*. This is an important characteristic to fuzzy complements and an attribute that will be revisited during the development of the fuzzy segmentation parameter selection tool.

5.2.2.2 Fuzzy Union

The fuzzy union operator, $\bigcup$, is used to describe both standard and non-standard union operations. The union operator is best described as a logical OR operation. The standard fuzzy union interpretation of OR is a maximum operation which results in the maximum value between two fuzzy sets. Assuming that fuzzy sets *B* and *C* are defined over the universal set *A*, the fuzzy union between *B* and *C* can be formalized by:

$$(B \bigcup C)(a) = \max[B(a), C(a)] \tag{5.5}$$

for all $a \in A$. The standard fuzzy union operation is depicted graphically in Figure 5.3 where the union between fuzzy set *Experienced* and its complement is shown.

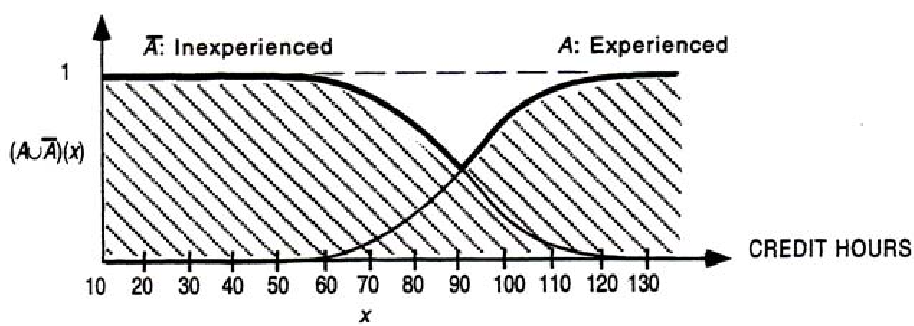


Figure 5.3
Union of fuzzy set *Experienced* and its complement (from Klir et al. [1997, p. 93]).

The union operation can be further complicated when dealing with fuzzy sets. Although the maximum operator is the standard union operator, other OR operations can be defined. These operations are collectively referred to as non-standard union operations.

One example of a non-standard union operator is referred to as the probabilistic OR operator and is defined in Matlab [The Mathworks, 2005] as:

$$(B \underset{prob}{\cup} C)(a) = probor[B(a), C(a)] = b + c - b \cdot c \tag{5.6}$$

for all $a \in A$, $b \in B$, and $c \in C$. Other non-standard OR operations are possible and find use depending upon the circumstances, but this research focussed solely on the above two definitions.

5.2.2.3 Fuzzy Intersection

The fuzzy intersection operator, $\cap$, is a logical AND operation. The standard fuzzy intersection operation is a minimum operation. Once again, assuming that fuzzy sets *B* and *C* are defined over the universal set *A*, the fuzzy intersection between *B* and *C* can be formalized by:

$$(B \cap C)(a) = \min[B(a), C(a)] \tag{5.7}$$

for all $a \in A$. The standard fuzzy intersection operation is depicted graphically in Figure 5.4 where the minimum between fuzzy set *Experienced* and its complement is shown.

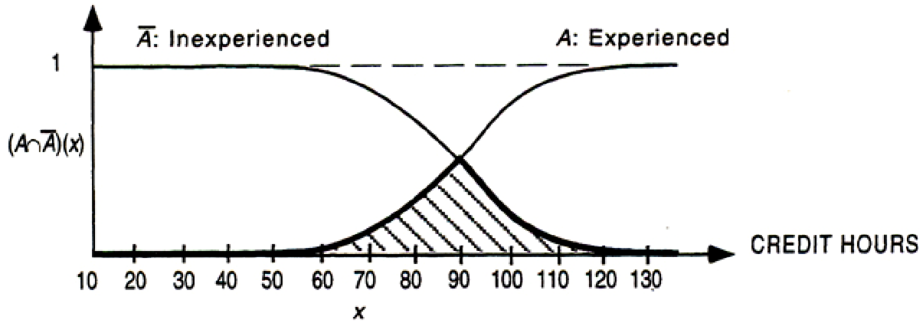


Figure 5.4
Intersection of fuzzy set *Experienced* and its complement (from Klir et al. [1997, p. 94]).

Once again, non-standard intersection operations are possible. This research used the non-standard product AND operator given by:

$$(B \underset{prod}{\cup} C)(a) = prod[B(a), C(a)] = b \cdot c \tag{5.8}$$

for all $a \in A$, $b \in B$, and $c \in C$. This research focussed specifically on the above two definitions for the AND operator.

5.2.2.4 Standard and Non-Standard Operations

To complete the discussion of fuzzy operators, it is necessary to understand why there is a distinction between standard and non-standard operations. Classical set theory has a number of properties such as distributivity, associativity, and commutativity. When working in the realm of fuzzy set theory, the lack of sharp boundaries defining fuzzy sets causes certain operations to fail to meet some of these classical properties. As a result, standard and non-standard fuzzy operations are defined by the properties that they maintain.

Standard fuzzy operations are defined as those operations that meet all the classical set properties except law of the excluded middle (union operation) and law of contradiction (intersection operation). Meanwhile, non-standard fuzzy operations fail to meet other properties as well [Klir et al., 1997]. Although standard operations perform satisfactorily in most applications, the "expressive power" of non-standard operations may offer advantages in some circumstances [Klir et al., 1997]. This research will use both types of operators to achieve the desired result.

5.2.3 Implication and Rule Bases

To this point, we have explored the concepts of fuzzy sets and fuzzy operations. Combining fuzzy sets using fuzzy operators using "if-then" statements creates rules. The "if" part of the statement, also called the "antecendent", is composed of one or more fuzzy sets combined using fuzzy operators. The "then" part of the statement is composed of a single fuzzy set called the "consequent". Once evaluated, the antecedent result is a single value that describes the firing strength of the rule. The process of applying this antecedent result to the consequent is known as implication.

Implication is carried out through the application of a fuzzy operator between the antecedent result and the consequent. Generally speaking, the result of implication is a modified fuzzy set in output space (see Figure 5.1). Although this is the most common practice, it is also possible that the consequent be a singleton (spike) in output space. In this case, the singleton can be defined by a constant, first order, or higher order function.

In the case of a constant function, the output singleton is stationary in output space. The only effect on the output for each rule is the firing strength. This simplification can work very well for specific applications. Linear functions offer the advantage that the singletons move around in output space as a first order function of the input elements. This permits additional flexibility at the cost of slightly increased complexity by allowing the output to adapt to the input. Finally, higher than first order functions are possible but offer little advantage at the cost of significant complexity [The Mathworks, 2005]. The use of constant singletons in output space instead of fuzzy sets is shown in Figure 5.5.

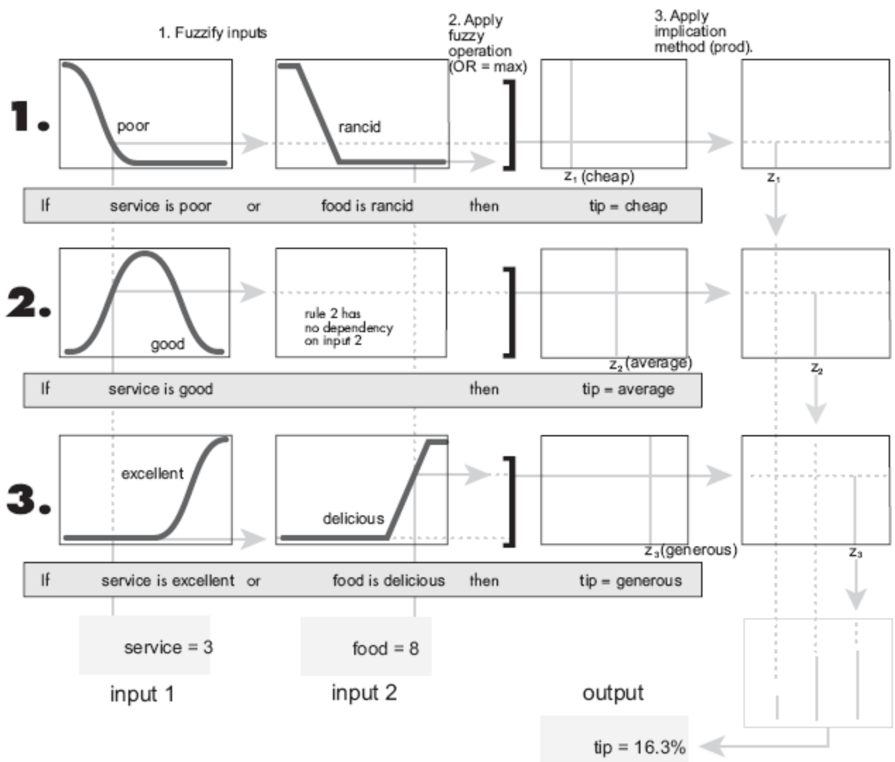


Figure 5.5
Using singletons in output space (from The Mathworks [2005, p. 2-79]).

To this point we have discussed the components that make up a single rule. The power of a fuzzy inference system, however, comes from the combination of a number of rules together. This set of rules is called a rule base and the interaction between the rules is called aggregation. A rule base needs only to be defined once, and can continually be applied as a control structure to the same situation. As the input changes, the results will change, but the same rule base will always be applied to a given situation.

5.2.4 Aggregation

Aggregation, also called inferencing, is the heart of the FIS. In this step, the output from all rules in the rule base are combined together to form a single fuzzy set or a set of singletons. The method of combination will vary according to the intended use of the output. The combination of outputs could be as simple as summation or as complicated as the user desires. Regardless of the method of combination, the result from this step must be converted into a single useful output value. This is the last step in the FIS and will be discussed next.

5.2.5 Defuzzification

The aim of defuzzification is to take the aggregated fuzzy result produced in the previous step and produce a single value that is representative of the combination of input rules. In the case of an aggregated fuzzy set, the output can be determined in a number of different ways. One of the most popular methods is to take the overall centroid value of the fuzzy set, but many other methods are also possible. If the aggregated result is a set of singletons, the defuzzification method is more restrictive. The weighted average or weighted sums are two useful approaches where the weights are defined by the firing strength of each singleton. With the defuzzification complete, the user now has a single definite result that is useful to the control application at hand.

5.3 Development of the Parameter Selection Tool

The success of the object-oriented approach to classification is highly dependent on the successful segmentation of the input image. Currently, eCognition relies heavily on user experience in combination with a trial and error approach to determine the appropriate parameters for segmentation. This is often a difficult and time-consuming process. A tool designed to aid the user in this regard would prove extremely useful.

To this point, we have explored fuzzy logic as a control methodology and can see it is a powerful tool given its ability to manage vague input and produce a definite output. This property, combined with its flexible and empirical nature, make this control methodology ideally suited to the task of segmentation parameter selection. The workflow and fuzzy inference systems to accomplish this task are developed in detail during the remainder of this chapter.

5.3.1 Design Requirements for the Proposed Tool

Recall from Chapter 4 that the major problems with parameter selection are: (1) determining the number of levels that should be extracted; (2) the selection of appropriate segmentation parameters for each level in a timely manner; and (3) a method of evaluation of segmentation results beyond that which is visually pleasing. Currently, eCognition is designed to provide "knowledge-free extraction" of objects through the selection of parameters based on the user's experience [Definiens Imaging GmbH, 2004b]. Once an object level is completed, the user must determine what it is that the objects best represent. Upon determining this, the level can be used for further segmentation by creating other object levels or classification if the objects represent land cover of interest. In many cases, different land cover types will require different object levels for optimal extraction, especially if shape features are to be used for classification.

A tool developed to address these issues should meet the following requirements:

a. Each execution of the tool is aimed at extracting one land cover type and results in one level of the object hierarchy;

b. Segmentation must be controlled and refined in an iterative manner based on an object model;

c. The tool must rely on an initial segmentation as a start state;

d. Scale, shape, and smoothness parameters must be determined;

e. Parameter selection must be reproducible; and

f. The tool must demonstrate reasonably fast and efficient performance.

The segmentation of an input image is performed on a number of different levels to permit objects of different scales to be extracted on their own level. By using this approach, objects can be classified on the level where the segments are the most meaningful and best represent the object of interest. This infers that the user must have a specific land cover class in mind when segmenting the image so that the parameters can be best estimated and then refined through trial and error. As a result, the fuzzy tool must aim to extract one particular land cover type each time it is executed. By running the tool a number of times, a hierarchy of object levels can then be developed.

To define a particular land cover type, modelling of the land cover object of interest would seem the logical approach. This method is supported by Hay et al [2003] whereby they hypothesized that the "intrinsic scale of the dominant landscape objects composing a scene" guide the selection of scale on multiple levels. To accomplish this, the analyst should define the model in a supervised manner by selecting the sub-objects (SO) that make up the dominant landscape object of interest or model object (MO). Object properties such as size, shape, tone, and texture can then be established and used to guide the segmentation process to a high quality result. This approach addresses the first two requirements above.

Selection of the sub-objects that make up the model object implies that segmentation has already been carried out. If not, the user would be forced to select all of the pixels that make up the object of interest. This would offer limited initial information to estimate the scale parameter and would be a tedious task for the user, especially for large objects. A more reasonable approach would be to start with an initial segmentation of the image to allow the user to select those objects that make up the object of interest. In addition, the scale parameter used for this initial segmentation would offer very useful information to aid in the estimation of the most appropriate scale parameter for the land cover type to be extracted. Finally, when establishing subsequent levels, the system must have the ability to build upon the previously extracted level.

To ensure that the initial segmentation is useful, it should be performed at a small scale with most weight on the spectral properties of the image. The small scale will ensure that the object of interest is over segmented. The focus on spectral properties will ensure that the initial segments are representative of only one land cover class. Together, these initial objects will provide the building blocks to extract the object of interest and will allow the user to model the exact object.

Finally, the most important parameters for segmentation are scale, shape, and smoothness. Although unique band weighting is also possible, the improvement to segmentation would come at the cost of significant complexity. Therefore, it is most important for the proposed system to determine the three primary parameters. In order to ensure the operational relevance of the proposed tool, the selection of scale, shape, and smoothness must be carried out in a manner that is reproducible and reasonably fast.

5.3.2 Proposed Workflow

Having outlined the design requirements, we can proceed to establish a workflow to meet these criteria. The proposed workflow for the fuzzy segmentation parameter selection tool is shown in Figure 5.6.

In accordance with this diagram the start state is an initial segmentation of the input image. This segmentation should be conducted using a small scale parameter with little or no weight given to the shape parameter. This approach produces an over segmented image with the emphasis on spectrally homogeneous objects. In this manner small details in the image, and more importantly the land cover object of interest, are retained.

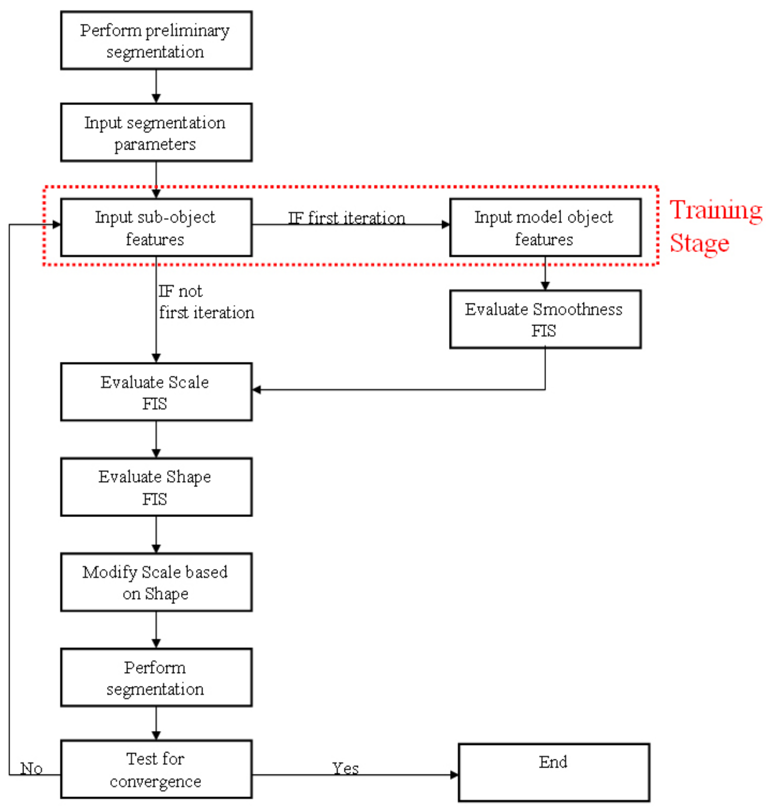


Figure 5.6
Proposed fuzzy segmentation parameter selection workflow

Once complete, the user must select the sub-objects (SO) that form the model object (MO) being extracted. During the first iteration, the union of all sub-objects will exactly define the model. This is the ideal case, but as the region merging routine progresses, this may cease to be true. A threshold must be established to determine the point at which a sub-object ceases to be considered part of the model-object. This is easily accomplished by ensuring a minimum fractional area of each sub-object falls inside the model object. In this manner, the set M of sub-objects m that form the model object can be formalized by:

$$M = \{\ m \mid [\mathrm{area}(m \cap \mathrm{MO}) \ / \ \mathrm{area}(m)] > \mathrm{T}\} \text{ for all } m \in I \qquad (5.9)$$

where T specifies the fractional area threshold, and I denotes the entire image. However, if at any point MO is completely inside one sub-object, then that sub-object will be the only object comprising the set M.

Using this definition for the sub-objects that form the model object, the user must input the current segmentation parameters, sub-object (SO) features, and model object (MO) features into the system (the definition of these features will be discussed in detail later). The system will use the SO features to evaluate the current segmentation status and compare these results to the desired final segmentation state described by the MO features. This comparison is conceptually based on discrepancy evaluation of image object quality thereby providing the theoretical foundation for this approach (see Zhang, 1996; Zhang, 1997). By using object feature discrepancy, smoothness, scale, and shape parameters can be estimated, each using their unique fuzzy inference system (FIS) to perform this operation. Due to the interrelationship between scale and shape, the estimated scale parameter is further modified as a function of the estimated shape parameter. This is necessary since the FIS features that describe scale are purely dependent on the spectral properties of the object, yet scale is a function of both spectral and shape characteristics (see Section 3.1.3.1). Finally, segmentation is performed using the estimated parameters and convergence to the model object solution is tested based on feature discrepancy measures. If not yet converged, the system will continue to iterate to a solution. Therefore, convergence will only be achieved once the result is of suitable quality as determined through feature discrepancy measures between the sub-object and model object based on scale and size comparison at each iteration.

This workflow was implemented using Matlab and the Fuzzy Logic Toolbox extension.

5.4 FIS Development

The first step in applying a fuzzy control structure to this problem requires the definition of input variables. In this application, the variables will be SO features that are representative of the current status of the segmentation process. In turn, these features will be used to guide the process to its successful completion. Selection of the appropriate features requires an in-depth understanding of the region-merging routine used by eCognition (see Section 3.1.3). Definition of these features for each FIS will be discussed individually in the following sections.

5.4.1 Scale FIS

Recall that region-merging in eCognition is based upon the notion that the "average heterogeneity of image objects weighted by their size should be minimized" [Definiens Imaging GmbH, 2004b]. Although heterogeneity change is a function of both spectral and shape properties, the effect of the latter on the overall heterogeneity calculation cannot be determined since it is not estimated when the scale parameter is determined. For this reason and to ensure that our scale parameter is as large as possible (see Section 4.1.1.2) we make our initial estimate of the scale parameter based solely on the spectral properties of the sub-objects in the initial segmentation. In fact, this simplification works very well since the spectral information is the primary information in the image and our initial segmentation is based almost entirely on spectral information.

Also recall from equation 3.1 that spectral heterogeneity change, $h_{spectral}$, is a function of individual spectral band weights, w_c. To ensure simplicity of the system is not compromised, the weight of each band will be set to unity. Hoffman [2001] suggests that this assumption is reasonable for most applications given the relatively high correlation between the different spectral bands in VHR imagery. With these simplifications made to reduce the inherent complexity of the scale parameter, we can proceed to feature definition for the scale FIS.

5.4.1.1 Proposed Feature Definitions

Determining the spectral features that will best monitor and guide the selection of the scale parameter is not an easy task. Based on experience using the eCognition software and equation 3.1, we know that spectral variance (texture) is the primary tool used to measure spectral heterogeneity. Within a user defined model object, texture can be described by the internal texture of each sub-object (pixel variance) as well as the texture resulting from the different spectral mean between sub-objects. Therefore, two fuzzy input variables are defined for the scale parameter FIS as developed in this research: (1) mean object texture, *Texture*, and (2) object stability, *Stability*. In this way, *Texture* will establish the internal sub-object feature and S*tability* will establish the external sub-object feature. Together, they will be used to estimate the current segmentation status as well as the final desired segmentation state.

Texture, as proposed in this research, is a feature defined by:

$$Texture(m \text{ objects}) = \frac{1}{n_{merge}} \sum_m \left[n_{obj_m} \cdot \frac{1}{c} \sum_c \sigma_c^{obj_m} \right] \tag{5.10}$$

where $\sigma_c^{obj_m}$ is the standard deviation of object m in spectral layer c, c is the number of spectral layers, n_{obj_m} is the number of pixels comprising object m, m represents the number of sub-objects comprising the model object, and n_{merge} is the number of pixels in the resulting merged object. Understanding that spectral variance is an important value in the calculation of $h_{spectral}$, and that spectral variance continues to grow with the size of the objects, this feature is a key indicator in determining the current state of segmentation.

The proposed *Stability* feature defines the spectral similarity between objects. Sub-objects that are spectrally homogeneous internally may be very different from each other. The greater the spectral difference between the sub-objects, the higher the scale will have to be to merge them. To ensure an appropriate definition for the *Stability* feature we will apply eCognition's built-in *Mean_Difference_to_Neighbors* feature as defined by [Definiens Imaging GmbH, 2004b]:

$$\Delta s_c^{obj_m} = \frac{1}{l} \cdot \sum_p \left[l_s^{obj_p} \cdot \left| \bar{s}_c^{obj_m} - \bar{s}_c^{obj_p} \right| \right] \tag{5.11}$$

where $\bar{s}_c^{obj_m}$ is the spectral mean value of layer *c* for the object of interest, $\bar{s}_c^{obj_p}$ is the spectral mean value of layer *c* of direct neighbour object *p*, *p* represents the number of objects that are direct neighbours to the object of interest, *l* is the border length of the object of interest, and $l_s^{obj_p}$ is the length of shared border between object of interest and direct neighbour object *p*. Using this feature we are able to define our own *Stability* feature to evaluate the similarity of each sub-object *m* to its neighbour objects. *Stability* in this research is defined as:

$$\mathit{Stability}(m \text{ objects}) = \frac{1}{m} \sum_m \left[\frac{1}{c} \sum_c \Delta s_c^{obj_m} \right] \tag{5.12}$$

where *m* represents the number of sub-objects.

5.4.1.2 Fuzzy Set and Rule Base Development

The *Texture* and *Stability* features defined above are applied to the sub-objects comprising the model object to evaluate the current segmentation status of the system. Using the same features and applying them to the model object can measure the segmentation state that we want to achieve. In doing so, these MO feature values play an important role in defining the membership functions. The shape of each membership function is a result of empirically evaluated success of the system. Therefore, if the system needs to be adjusted to produce better estimates for the scale parameter, the membership function can simply be modified until the FIS produces improved results. Both *Texture* and *Stability* membership functions are graphically defined in Figures 5.7 and 5.8.

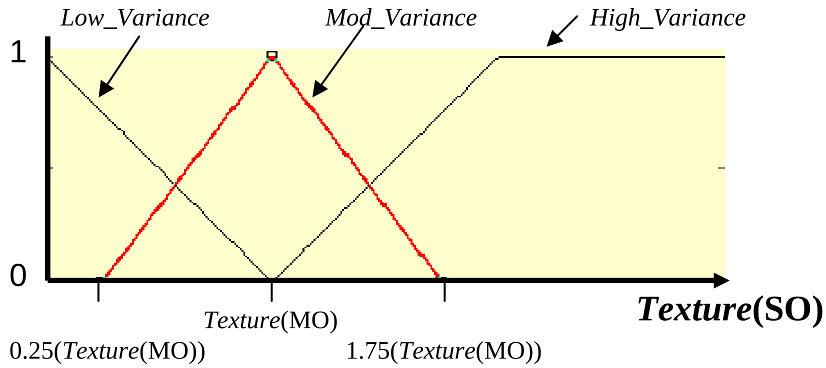


Figure 5.7
Texture feature membership functions

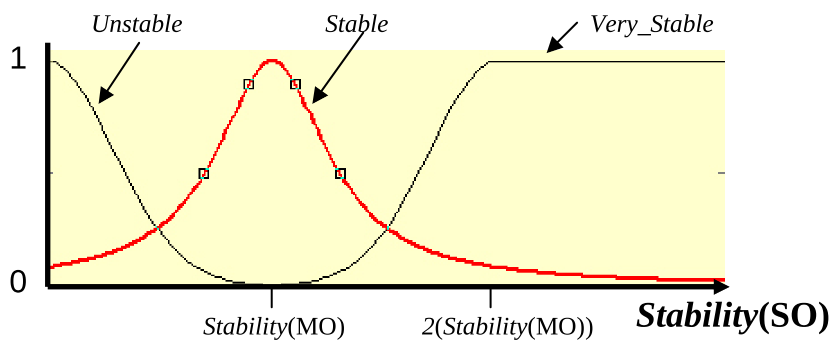


Figure 5.8
Stability feature membership functions

With membership functions defined, the rules forming the rule base are formed. The rules for the scale FIS as proposed in this research are:

a. $\mu_{Increase} = [\ \mu_{Low\_Variance}(Texture(SO)) \cap \mu_{Unstable}(Stability(SO))\ ]$

b. $\mu_{Increase} = [\ \mu_{Low\_Variance}(Texture(SO)) \cap \mu_{Stable}(Stability(SO))\ ]$

c. $\mu_{Increase} = [\ \mu_{Mod\_Variance}(Texture(SO)) \cap \mu_{Unstable}(Stability(SO))\ ]$

d. $\mu_{Maintain} = [\ \mu_{Low\_Variance}(Texture(SO)) \cap \mu_{Very\_Stable}(Stability(SO))\ ]$

e. $\mu_{Maintain}$ = [$\mu_{Mod\_Variance}$ (*Texture*(SO)) $\cap$ μ_{Stable} (*Stability*(SO))]

f. $\mu_{Maintain}$ = [$\mu_{High\_Variance}$(*Texture*(SO)) $\cap$ $\mu_{Unstable}$(*Stability*(SO))]

g. μ_{Reduce} = [$\mu_{Mod\_Variance}$ (*Texture*(SO)) $\cap$ μ_{Very_Stable} (*Stability*(SO))]

h. μ_{Reduce} = [$\mu_{High\_Variance}$ (*Texture*(SO)) $\cap$ μ_{Stable} (*Stability*(SO))]

i. μ_{Reduce} = [$\mu_{High\_Variance}$ (*Texture*(SO)) $\cap$ μ_{Very_Stable} (*Stability*(SO))]

During successive iterations, the singletons that compose the three output membership functions (*Increase*, *Maintain*, and *Reduce*) are shifted. Since the singletons do not move during the iteration they are considered zero order functions (constant). The three output membership functions are formally defined as:

a. μ_{Reduce} = *Reduce*(x);

b. $\mu_{Maintain}$ = *Maintain*(y); and

c. $\mu_{Increase}$ = *Increase*(z).

In this case, x is defined as the scale from the previous iteration, y is the current scale, and z is a predicted scale. An element of history is ensured by using the previous scale to define μ_{Reduce} while a prediction is made as to the next scale according to:

$$z = 2y - x + \sqrt{n_{merge}} \cdot \sqrt{m} \tag{5.13}$$

where n_{merge} is the number of pixels comprising the merged object and m is the number of sub-objects forming the model object.

5.4.1.3 Aggregation and Defuzzification

The use of constant membership functions in output space instead of a modified fuzzy set permits aggregation and defuzzification to be completed in one step. In the scale FIS, this combined step is performed using a weighted average of x, y, and z where each value (location) is weighted by the membership value determined from the firing strength of each rule in the rule base. The result is a single scale value that is the estimate for the next iteration.

5.4.2 Shape FIS

The balance between spectral and spatial information in the calculation of the scale parameter is a critical one. Recall from Section 4.1.1.2 that the spectral information should be weighted as much as possible, while using only as much shape information as necessary. This makes perfect sense since spectral information is the primary information in the image. However, as objects grow larger shape plays an increasingly important role. This is particularly true if one or more of the sub-objects that form the object of interest have significantly different spectral information. In this case, the region-merging routine may tend to merge with objects outside the object of interest if they are spectrally similar. To prevent this from happening, shape information becomes increasingly important to successful segmentation, but too much shape information and we lose our connection to the spectral information in the image. A correct balance must be determined to achieve a visually convincing result.

5.4.2.1 Proposed Feature Definitions

Defining features that aid in the prediction of an appropriate shape parameter is not easy. Consequently, three different features were defined for this task. The first two features focus on local properties. In other words, the properties of sub-objects as they relate to the model object. The primary reason for these features is to identify any particularly large spectral difference or size difference between the sub-objects. Such occurrences can have adverse effects on merging when relying only on spectral information as a result of the texture information they contain. The last feature focuses on a global property and emphasises the importance of sub-object absolute size to the determination of the shape parameter. The larger that sub-objects grow, the more important shape becomes. Together, these features will determine the shape parameter that best suits the situation.

The first proposed feature determines which sub-object, m, has the maximum spectral difference compared to the desired model object, M. The identified sub-object is then used to calculate the *Spectral_Mean* feature. This feature is particularly important for urban areas where problems often arise when one object (ie. air conditioning unit) may be particularly bright while the rest of the rooftop is dark. The larger the spectral difference between the one object and the average rooftop value, the more difficult it may be to merge the objects together based on spectral properties. Instead, maintaining the overall shape of the roof may play increased importance to achieve a satisfying result.

Given the set *M*, composed of *m* sub-objects, the subset of objects, A, which has the largest mean spectral difference as defined in this research is given by:

$$A=\{\ a \mid a = m \text{ for all objects } m \in M \text{ where } \max\left\{\frac{1}{c}\sum_{c}\left|\bar{s}_c^{obj_m} - \bar{s}_c^{obj_M}\right|\right\} \text{ is True}\} \qquad (5.14)$$

where $\bar{s}_c^{obj_m}$ is the spectral mean value of layer *c* for the sub-object of interest, $\bar{s}_c^{obj_M}$ is the spectral mean value of layer *c* for the model object, and *c* is the number of spectral layers. In all likelihood, the set A will contain a single object unless two or more objects are found with an identical maximum mean spectral difference. If this should happen, the object with the largest size should be selected. In any case, the object with the maximum mean spectral difference is used to determine the proposed S*pectral_Mean* feature given by:

$$\textit{Spectral\_Mean}(m \text{ objects}) = \frac{1}{c}\sum_{c}\bar{s}_c^{obj_a} \text{ for object } a \in A. \qquad (5.15)$$

The second feature assesses the size of the object identified in equation 5.5. This feature explores the size difference between sub-object *a* and the average sub-object size. This aids in determining the degree to which shape should be increased to successfully merge the sub-objects. If the air conditioning unit from the previous example is only small, then there is an increased chance that it will merge with the surrounding objects based on spectral properties. However, if it is large in size, then the texture change is large and may not merge well with surrounding objects based solely on spectral properties. In this case, shape takes on greater importance.

Size_Difference feature as proposed in this thesis is defined by:

$$Size\_Difference(m \text{ objects}) = \left| \left(\frac{1}{m} \sum_{m} n_{obj_m} \right) - n_{obj_a} \right| \tag{5.16}$$

where *m* is the number of objects forming the model object, n_{obj_m} is the number of pixels comprising object *m*, and n_{obj_a} is the number of pixels forming object *a*, where object *a* is the object that satisfies equation 5.14.

Finally, the global largest size feature is used to monitor the growth of sub-objects. In general, the larger an object grows the more shape is required to achieve a visually convincing result. The proposed *Lg_Size* feature is defined as:

$$Lg\_Size(m \text{ objects}) = \max\{n_{obj_m}\} \text{ for all objects } m \in M \tag{5.17}$$

where n_{obj_m} is the number of pixels comprising object *m*.

5.4.2.2 Fuzzy Set and Rule Base Development

The membership functions comprising the above features are graphically shown in Figures 5.9 through 5.11.

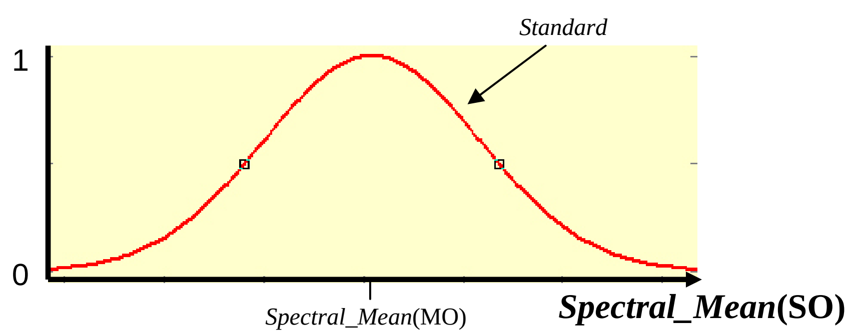


Figure 5.9
Spectral_Mean feature membership function

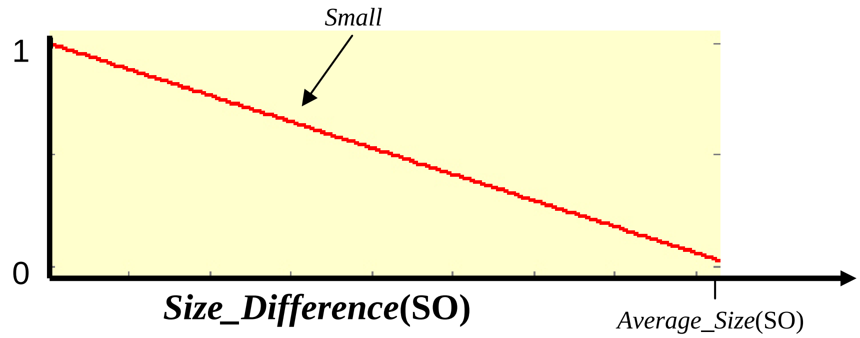


Figure 5.10
Size_Difference feature membership function

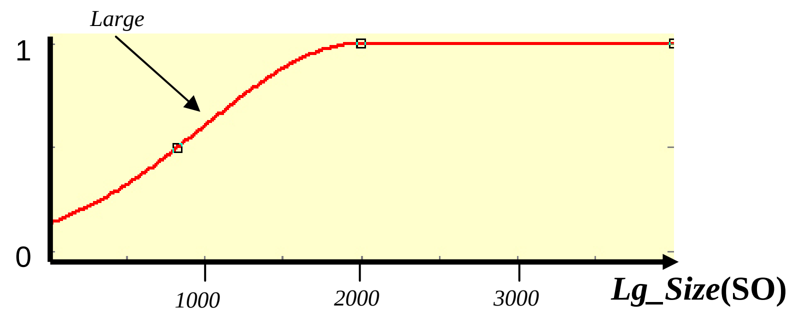


Figure 5.11
Lg_Size feature membership function

In this instance, there is only one membership function defined for each feature. By using the logical NOT or compliment operation, we can create other membership functions without defining them outright. With these membership functions defined, the rules forming the rule base are created. The rules for the shape FIS are:

a. $\mu_{\text{Less}} = [\ \mu_{\text{Standard}}(\textit{Spectral\_Mean}(\text{SO})) \underset{prod}{\cap} \mu_{\text{Small}}(\textit{Size\_Difference}(\text{SO}))\ ]$

b. $\mu_{\text{Average}}=[\mu_{\neg\,\text{Standard}}(\textit{Spectral\_Mean}(\text{SO})) \underset{prod}{\cap} \mu_{\neg\,\text{Small}}(\textit{Size\_Difference}(\text{SO}))]$

c. $\mu_{\text{More}}= [\ \mu_{\text{Large}}(\textit{Lg\_Size}(\text{SO}))\ ]$

The singletons that compose the three output membership functions (*More*, *Average*, and *Less*) remain constant at all times since the universe of discourse for the shape parameter is limited to the interval [0,0.9]. The maximum value for shape is 0.9 because at least part of the heterogeneity criteria has to come from the image itself (ie. spectral information). The singletons were balanced in the output space occupying positions of 0.1, 0.5, and 0.9 ensuring at least a little of both shape or spectral criteria in the calculation of heterogeneity change, even at the extremes. The three output membership functions are defined as:

a. $\mu_{\text{Less}} = \textit{Less}(0.1)$;

b. $\mu_{\text{Average}} = \textit{Average}(0.5)$; and

c. $\mu_{\text{More}} = \textit{More}(0.9)$.

5.4.2.3 Aggregation and Defuzzification

For the shape FIS, aggregation and defuzzification is carried out by means of a weighted average once again. Defuzzification is not so apparent in this case since the result is fuzzy itself and is used directly as a weight parameter in the calculation of the heterogeneity.

5.4.3 Smoothness FIS

In the last section, we discussed the critically important balance between spectral and shape heterogeneity. As the importance of shape increases, the smoothness parameter grows in importance since smoothness and compactness describe the shape of an object. If the emphasis is placed on object compactness, then objects are more likely to merge if they form a compact shape as a result of the reduced heterogeneity change in the object merge. As a result, the tendency will be to grow compact objects.

Different from the spectral versus shape relationship, compactness versus smoothness are not mutually exclusive terms. An object can be both compact and smooth. The smoothness parameter simply identifies which is the most important to user by permitting the selection of this weighting element.

According to the workflow in Figure 5.6, the smoothness FIS is evaluated only once and the parameter is left unchanged throughout for the duration of the remaining iterations. The reason for this is that the shape properties of the model object constitute the only important factor to the determination of the smoothness parameter. If the model object is compact, then the emphasis should be placed on compactness. The model object does not change and so the weight value associated to compactness does not change either. The parameter that does change is the overall shape parameter, and this will affect the compactness of the objects that result. Therefore, the smoothness parameter is calculated only once and its importance is modified for each iteration using the shape parameter.

5.4.3.1 Proposed Feature Definitions

Recall from equation 3.3 that a compact object conceptually describes a circle with compactness increasing as the radius increases. When dealing with pixels, however, the ideal compact object becomes a square due to the difficulty synthesising a circular form from square pieces. Also recall from equation 3.4 that an ideal smooth object is formed by a rectangle. Using these two equations, we will proceed to identify features that describe these different forms and in this way, determine which description is most important to achieving the model object form.

Smoothness is described using a black-box eCognition feature called Rectangular Fit. This feature creates a rectangle of the same area and length-to-width ratio as the object being rated. Once complete, the rectangle is fit to the object and the object area outside the rectangle is compared to the object area inside [Definiens Imaging GmbH, 2004b]. The fit is then described with a value between 0 (no fit) and 1 (perfect fit) and constitutes the *Rect_Fit* feature that will be employed in this FIS.

Compactness is more easily defined using the ratio of the object perimeter to the object area. This feature is defined identically to the definition of compactness used by eCognition for segmentation. The *Compact* feature is defined mathematically as:

$$Compact(\mathrm{MO}) = \frac{l}{\sqrt{n_{obj_M}}} \tag{5.18}$$

where l is the model object's border length and n_{obj_M} is the number of pixels (area) of the model object.

5.4.3.2 Fuzzy Set and Rule Base Development

The membership functions comprising the above features are graphically shown in Figures 5.12 and 5.13. Independent membership functions add to the flexibility of the overall system. This was particularly important in this FIS since objects can be both smooth and compact. Using the compliment, a change in one membership function results in a change in the others, but with this approach, the membership functions could be modified independently. This demonstrated reasonable results in this FIS.

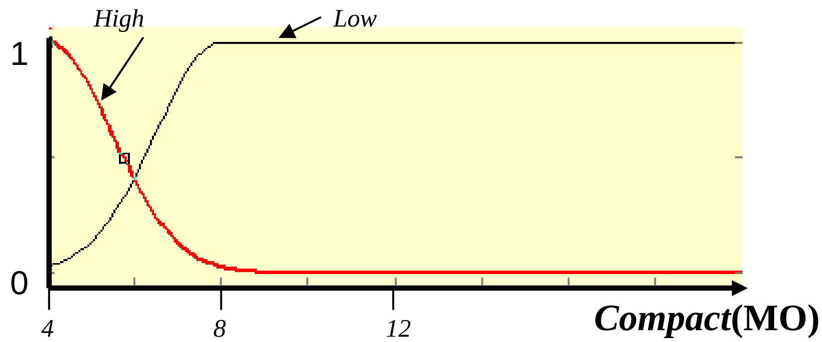


Figure 5.12
Compact feature membership functions

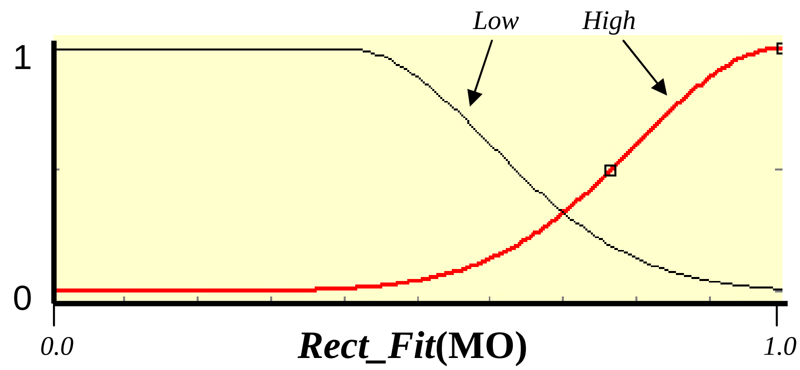


Figure 5.13
Rect_Fit feature membership functions

The rules for this FIS are:

a. $\mu_{Increase}$ = [μ_{High}(*Rect_Fit*(MO)) $\cap$ μ_{Low}(*Compact*(MO))]

b. $\mu_{Maintain}$ = [μ_{High}(*Rect_Fit*(MO)) $\cap$ μ_{High}(*Compact*(MO))]

c. $\mu_{Decrease}$ = [μ_{Low} (*Rect_Fit*(MO)) $\cap$ μ_{High}(*Compact*(MO))]

d. $\mu_{Decrease}$ = [μ_{Low} (*Rect_Fit*(MO)) $\cap$ μ_{Low}(*Compact*(MO))]

The singletons that compose the three output membership functions (*Increase*, *Maintain*, and *Decrease*) remain constant at all times since the universe of discourse for smoothness is limited to the interval between 0 and 1. Through experience with the software and as a result of the literature review, it was decided that compactness on the order of 0.2 is an average value and exhibits reasonable results. Therefore, the three output membership functions are defined as:

a. $\mu_{Decrease}$ = *Decrease*(0.0);

b. $\mu_{Maintain}$ = *Maintain*(0.2); and

c. $\mu_{Increase}$ = *Increase*(1.0).

5.4.3.3 Aggregation and Defuzzification

For the smoothness FIS, aggregation and defuzzification are carried out the same way as with all previous FISs. A weighted average of each singleton in output space is assessed and the defuzzified result is used to guide segmentation to its successful conclusion.

5.4.4 Scale Modification, Segmentation, and Convergence

In section 5.4.1, we defined two features based on object spectral properties to guide the selection of an appropriate scale parameter. In reality, the fusion value is a function of both shape and spectral properties. The rate of change of h_{shape} with respect to object size, however, is much larger than the rate of change of $h_{spectral}$. The resultant scale value calculated in the scale FIS is appropriate for a fusion value calculated solely on the basis of spectral properties, but with part of the fusion value based on shape, the objects grow too quickly and soon become too large.

To resolve this problem, the scale value must be modified to account for the shape parameter determined in the shape FIS. This modification is defined by:

$$\textit{Modified Scale Parameter} = (1 - w) \cdot \textit{Scale} \tag{5.19}$$

where *Scale* is the parameter determined in the scale FIS, and *w* is the shape parameter determined in the shape FIS.

Segmentation is carried out using the three primary segmentation parameters as determined in each FIS. Once completed, the convergence to the model object is evaluated based on the change in scale from the last iteration and the difference between model object and sub-object size. If these values fall under a specified threshold, the system is considered to have converged and the segmentation process is terminated.

Chapter 6

Implementation of the Developed Parameter Selection Tool

Knowledge must come through action; you can have no test which is not fanciful, save by trial.

[Sophocles]

6.1 Data Set and Land Cover Objects

To demonstrate the application of the fuzzy segmentation selection tool we will use the pan-sharpened data set of the suburban scene. Pan-sharpened data was selected over original multispectral due to the challenge presented by the increased information content and the pleasing results obtained by the pan-sharpened data in Chapter 4. Furthermore, the suburban scene was selected over the rural scene as a result of its complexity and the importance that shape plays in a complex and spectrally confusing urban environment. The tool as proposed here will be most useful in these difficult situations.

The implementation of this tool will focus on four separate land cover objects, each with their own unique attributes. The four land cover objects will include (Figures 6.1 through 6.4): (1) a high contrast building; (2) a low contrast building with shadow; (3) a ball diamond; and (4) a tree. Each land cover object is shown with its initial segmentation completed. The sub-objects making up the model object are highlighted in red.

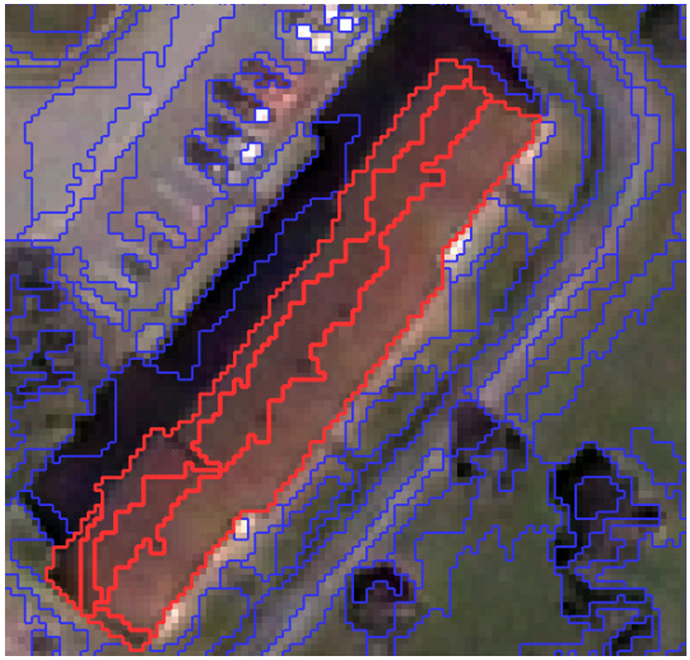


Figure 6.1
Initial segmentation of a high contrast building

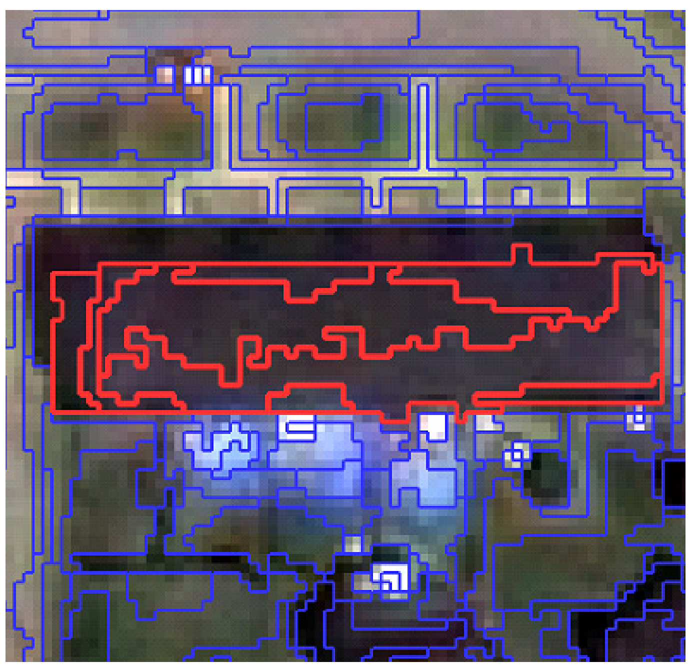


Figure 6.2
Initial segmentation of a low contrast building

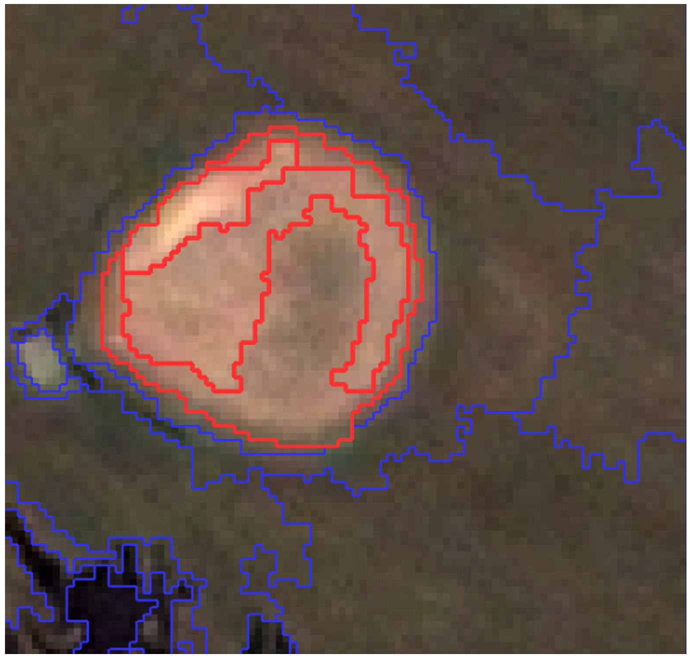


Figure 6.3
Initial segmentation of a ball diamond

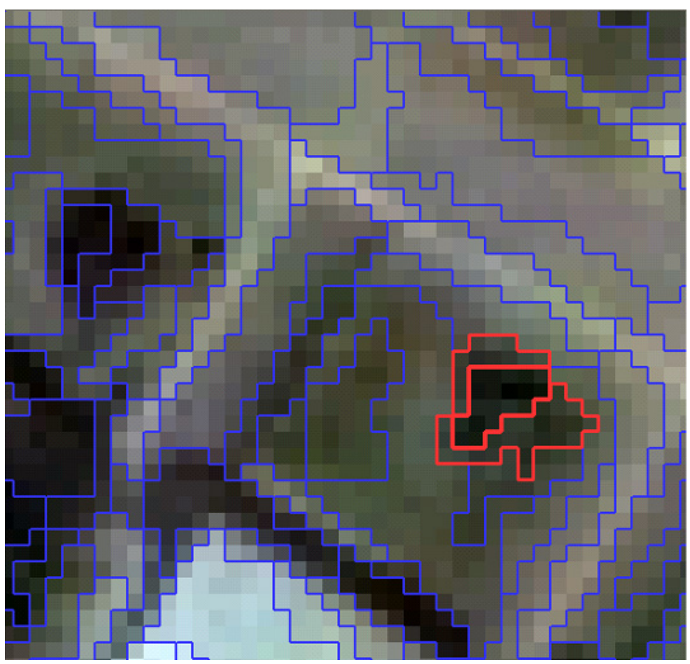


Figure 6.4
Initial segmentation of a tree

6.2 Implementation and Results

6.2.1 Initial Segmentation

In the initial segmentation, the objects of interest are oversegmented. The parameters for this initial segmentation are user selected, but ensure that the emphasis is placed on the spectral properties of the objects during this initial segmentation. The resulting sub-objects are small and spectrally homogeneous, retaining the detail of each object of interest intact. For example, the corners of the buildings are well defined in Figures 6.1 and 6.2, the shadow can be separated from the low contrast building in Figure 6.2, the turf is separate from the soil in the Figure 6.3, and the tree is distinctly separated from the surrounding grass in Figure 6.4. The parameters for these initial segmentations are shown in Tables 6.1 through 6.4 as the first iteration.

Table 6.1
Segmentation parameters for object in Figure 6.5

Parameter	**Iteration**			
	1	**2**	**3**	**4**
Number of sub-objects	6	2	2	1
Scale	25	52	85	120
Shape	0.1	0.723	0.410	0.410
Smoothness	0.1	0.868	0.868	0.868

Table 6.2
Segmentation parameters for object in Figure 6.6

Parameter	**Iteration**			
	1	**2**	**3**	**4**
Number of sub-objects	8	1	1	1
Scale	20	54	40	32
Shape	0.1	0.585	0.511	0.533
Smoothness	0.1	0.399	0.399	0.399

Table 6.3
Segmentation parameters for object in Figure 6.7

Parameter	Iteration	
	1	**2**
Number of sub-objects	3	1
Scale	50	76
Shape	0.1	0.621
Smoothness	0.1	0.248

Table 6.4
Segmentation parameters for object in Figure 6.8

Parameter	Iteration	
	1	**2**
Number of sub-objects	3	1
Scale	15	29
Shape	0.1	0.236
Smoothness	0.1	0.335

The challenge at this point is the selection of the appropriate segmentation parameters to permit the merging of sub-objects with each other while preventing the merging of the sub-objects with other objects belonging to different regions. This task is accomplished in the fuzzy tool through supervised training combined with the FISs as developed in Chapter 5. This process will be discussed next.

6.2.2 Parameter Determination

Once the initial segmentation is complete, employing the fuzzy segmentation parameter selection tool to perform the segmentation achieves very good results with relatively few iterations. To extract a specific land cover type, the user must simply select the objects that form the land cover object of interest. This step is the training stage and once complete, the selection of parameters and evaluation of subsequent iterations is performed automatically using the FISs developed in the previous chapter. The methodology simulates human decision making in an automated fashion, saving the user time, while not requiring a great deal of previous experience using the software.

With the exception of the first iteration where the user must estimate the initial segmentation parameters, the parameters selected by the proposed tool are consolidated in Tables 6.1 through 6.4. These results are shown in Figures 6.5 through 6.8.

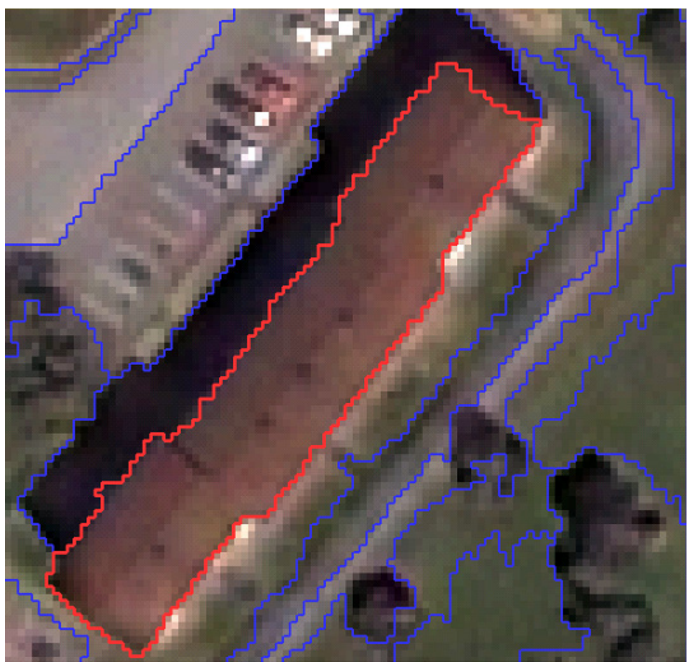


Figure 6.5
Extraction of high contrast building in four iterations (proposed method)

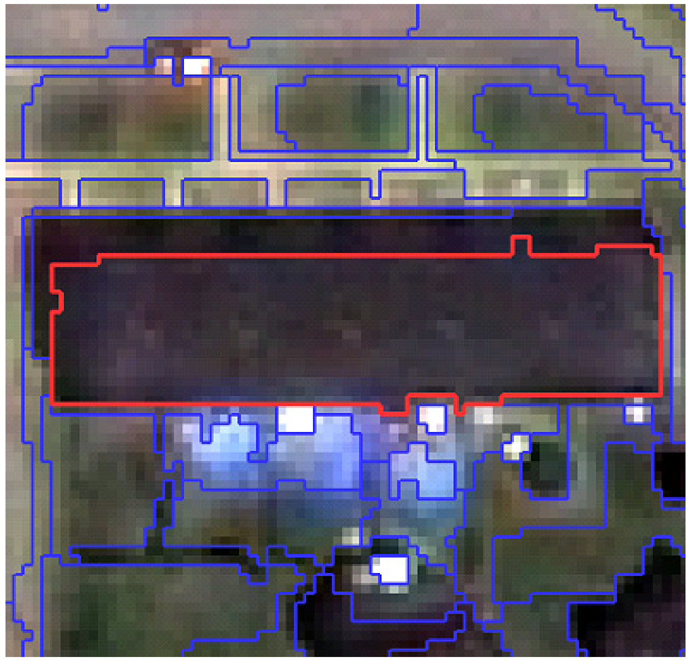


Figure 6.6
Extraction of low contrast building in four iterations (proposed method)

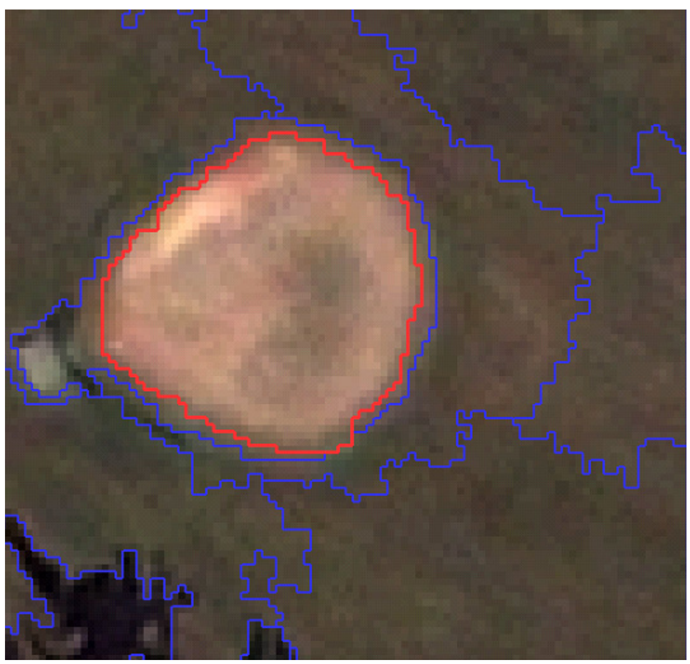


Figure 6.7
Extraction of ball diamond in two iterations (proposed method)

Figure 6.8
Extraction of tree in two iterations (proposed method)

6.3 Improvements over Trial and Error Approach

To demonstrate the improvements of the developed segmentation tool, the current state-of-the-art segmentation approach was used to segment the same land cover objects. In general, two significant improvements have been achieved: (1) segmentation parameter selection has been simplified through the use of the proposed tool; and (2) improved efficiency is achieved using the fuzzy tool by producing convincing segmentation results in a fast and automated manner.

6.3.1 State-of-the-Art Trial and Error Approach

Without applying the proposed fuzzy tool, scale, shape and smoothness parameter selection is carried out by the user through a trial and error process. The initial selection of these parameters is based on user experience and the general guidelines outlined in section 4.1.1.2. Subsequent iteration is then based upon the results of the previous trial.

Employing this approach, the user visually assesses subsequent segmentations to determine which parameters need to be changed. This approach is very qualitative in nature and inefficient since it requires user intervention at each step. Compounding these issues is the vagueness associated with the parameter names and through a visual assessment, it is difficult to determine degree of smoothness or shape and the appropriate scale that is required. Although not mentioned in the user manual provided by Definiens Imaging, theoretically, the user could resort to an evaluation of quantitative features, but this would require the definition of these features and further user intervention at each level. In the end, this extra work may provide little help unless these feature values can be evaluated in a systematic manner and linked to the segmentation parameters. Although the trial and error method is conceptually quite simple, iteratively improving the results is difficult when one cannot establish which parameters should be changed and by how much.

6.3.2 Ease of Operation of Proposed Tool

Employing the state-of-the-art trial and error approach, user intervention is required after every iteration to carry out the following tasks:

a. visually evaluate the segmentation;

b. decide whether to build upon the level or delete it;

c. decide which segmentation parameters should be changed and by how much to achieve the desired result.

This is a complex and time-consuming process and is especially difficult for user with little experience with the software and its underlying processes. As one experiments with the data set deleting the segmentation, and changing one or more of the parameters is often the best choice. As identified by Schiewe et al [2001], achieving the initial segmentation is relatively easy, but iteratively refining it using these combined parameters is very difficult. As a result, the trial and error process is far from simple.

The proposed fuzzy tool is able to perform this task in an automated manner once it has been trained by the user. The training routine is simple and straight forward requiring the user to simply select the objects that make up the land cover object of interest. Once complete, the system relies on quantitative measures to estimate the appropriate parameters, tests the resulting segmentation with respect to the desired outcome, and continues in this fashion to achieve a high quality result. For both the new and experienced user, the simplification offered by the proposed system offers a great advantage and lends itself well to the operationalization of the object-based approach to classification.

6.3.3 Improved Efficiency

The proposed fuzzy tool offers a significant advantage in terms of efficiency as well. High quality results are achievable using both trial and error or the proposed tool. However, in a comparable time as it takes the proposed system to converge to a solution, a new user would likely have had little opportunity to try more than a couple of iterations. The efficiency advantage is obvious.

Figures 6.9 through 6.12 demonstrate some of the problems and successes inherent in the trial and error approach. The success of this approach is a function of the object's properties, its surroundings, user knowledge, and chance.

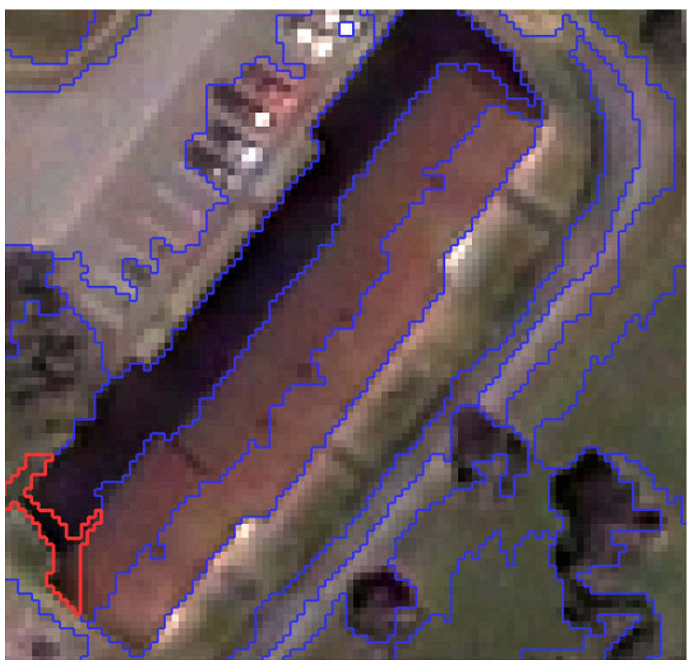


Figure 6.9
Sub-objects of building merge with outside regions (trial and error)

Figure 6.10
Sub-objects of building merge with building’s shadow (trial and error)

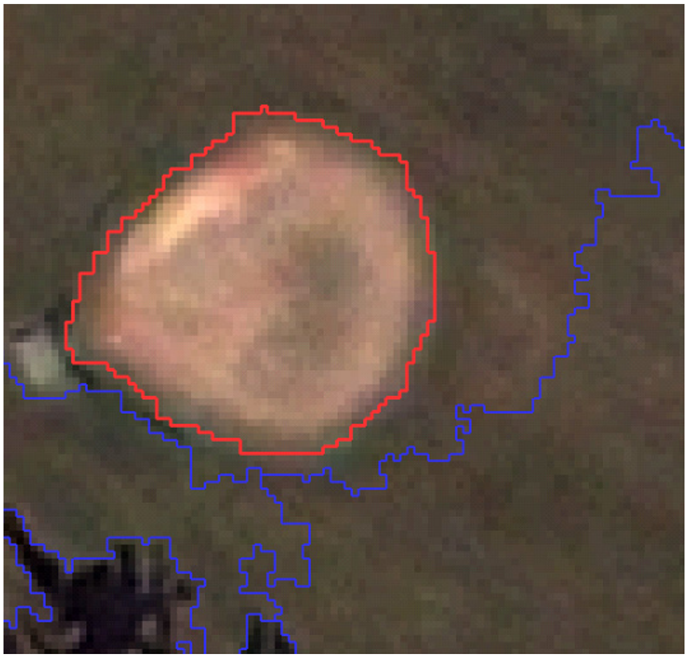


Figure 6.11
Successful extraction but large degree of object merging elsewhere (trial and error)

Figure 6.12
Successful extraction but parameters not applicable across image (trial and error)

Figure 6.9 shows how sub-objects can be merged with other outside regions. This is clearly represented by the object that contains the corner of the building, part of the building's shadow, and a part of the grass surrounding the building. As a result, this object cannot be properly classified, and it affects the quality of the building extraction. In a similar length of time, the building can be well extracted using the proposed fuzzy tool as shown in Figure 6.5.

A similar problem occurs in Figure 6.10 where sub-objects comprising a low contrast building are merged with the building's shadow. This is evident at the left hand side of the image where part of the building has been merged with the object representing the building's shadow. Once again, a lower quality result is achieved through trial and error in a similar timeframe as the proposed tool converges to a high quality result.

Figure 6.11 demonstrates successful extraction based upon the trial and error process but shows a great deal of object merging elsewhere in the image. This is particularly evident toward the top part of the image where all the grass objects have been merged as compared to Figure 6.7. This result is reasonable in this case, but arguably a better result extracts an object of interest while resulting in less object merging elsewhere so that successive object levels can be built upon this level. The proposed tool aims to achieve object extraction while minimizing object merging elsewhere in the image for this reason.

Finally, Figure 6.12 demonstrates successful extraction of the tree as highlighted in red, but the segmentation parameters do not apply well to other nearby trees. This can be seen in the case of the tree in the upper left quadrant of the figure where the tree is merged with the surrounding grass. The proposed fuzzy tool aims to adequately balance the spectral and shape parameters to ensure their applicability across the image. This is the case in Figure 6.8 where the fuzzy tool selected parameters that are applicable to all trees in the image.

Overall, the proposed tool demonstrates improved efficiency over the trial and error approach by converging to high quality results, often faster than trial and error, and does so in a simplified manner suitable for the first time user.

Chapter 7

Assessment of Results

When I tell the truth, it is not for the sake of convincing those who do not know it, but for the sake of defending those that do.

[William Blake]

This chapter will focus on the evaluation of the results achieved in Chapter 4 and Chapter 6. To accomplish this, an explanation of the assessment metrics for a comparison between UNB Pan-Sharpened and multispectral classification results will be outlined followed by the assessment. Similarly for the segmentation parameter selection tool, a description of assessment criteria will be covered followed by the evaluation of the results.

7.1 Assessment of Pan-Sharpened and Multispectral Results

The object-oriented approach to land cover classification is an approach that shows promise with its ability to manage the attributes of modern VHR sensor data and, more specifically, the increased information content of pan-sharpened imagery. In Chapter 4 we implemented both original multispectral imagery and pan-sharpened imagery for the classification task to explore the accuracy achievable using each data set. This section will focus on evaluating the results achieved in Chapter 4 both qualitatively and quantitatively.

7.1.1 Visual Assessment

Object-based classification is carried out in two distinct stages, those being segmentation and classification. Since the result of the classification stage relies on the success of the segmentation stage, a visual assessment would not be complete without commenting on the results of both stages. These assessments follow in the next two sections.

7.1.1.1 Segmentation

Even though segmentation has been an area of significant research, segmentation evaluation techniques have received little attention [Zhang, 1996]. Definiens Imaging [2004b] suggests that "a strong and experienced source for the evaluation of segmentation techniques is the human eye," arguing that even quantitatively assessed segmentations will not be convincing if they do not appear visually pleasing to the user. This was the qualitative evaluation method employed for the segmentation part of this research.

For both scenes, segmentation at each of the four levels was carried out using trial and error until a visually convincing result was attained. For the purpose of classification, the visual assessment focussed on ensuring the segmentation resulted in objects that:

a. separated the appropriate land cover classes;

b. well represented the shape of the different land cover objects; and

c. formed a hierarchy in which each class was appropriately represented in at least one level.

The separation of the different regions was critical to classifying the different objects since objects cannot be successfully classified if they are composed of more that one land cover class. The shape of the objects was an important aspect of object-oriented classification that was difficult to obtain, but critical to taking full advantage of this methodology. Finally, each class must be best represented in at least one level in order to be successfully extracted. The remaining levels contribute to the extraction at this level and class refinement using the top-down approach.

Achieving these criteria by successive iteration and visual assessment was a very time-consuming process for both scenes. This was particularly the case for the complex suburban scene where layer weights were adjusted in addition to scale, shape, and smoothness parameters. The rural scene averaged approximately 10 iterations per level to achieve the final segmentation. For the suburban scene, this increased to an average of about 15. Between successive iterations for a particular level the analyst was required to visually evaluate the segmentation and make a judgement as to the parameters that ought to be changed. In order to follow the changes, one parameter at a time needed to be adjusted. The end result was four visually convincing levels of image objects; however this was achieved at the cost of a great deal of time and effort.

7.1.1.2 Classification

Visual assessment of the classification results for both rural (Figures 4.13 through 4.16) and suburban (Figures 4.17 through 4.20) scenes are generally pleasing. It is immediately obvious that different land cover types appear to have been successfully segmented and classified. The outlines of the buildings, roads, and water all appear to have been extracted reasonably well. In addition, it is apparent that the object-oriented approach dealt particularly well with the high information content of both original and pan-sharpened data sets as there is no sign of the salt and pepper effect generally associated with traditional pixel-based classification methods. Therefore, on a small scale the classification appears accurate, but to get a true visual appreciation of the classification differences, a large scale inspection using an image subset would be useful.

For this purpose, the classification of image subsets (Figures 2.3 through 2.6) are displayed in Figures 7.1 through 7.8.

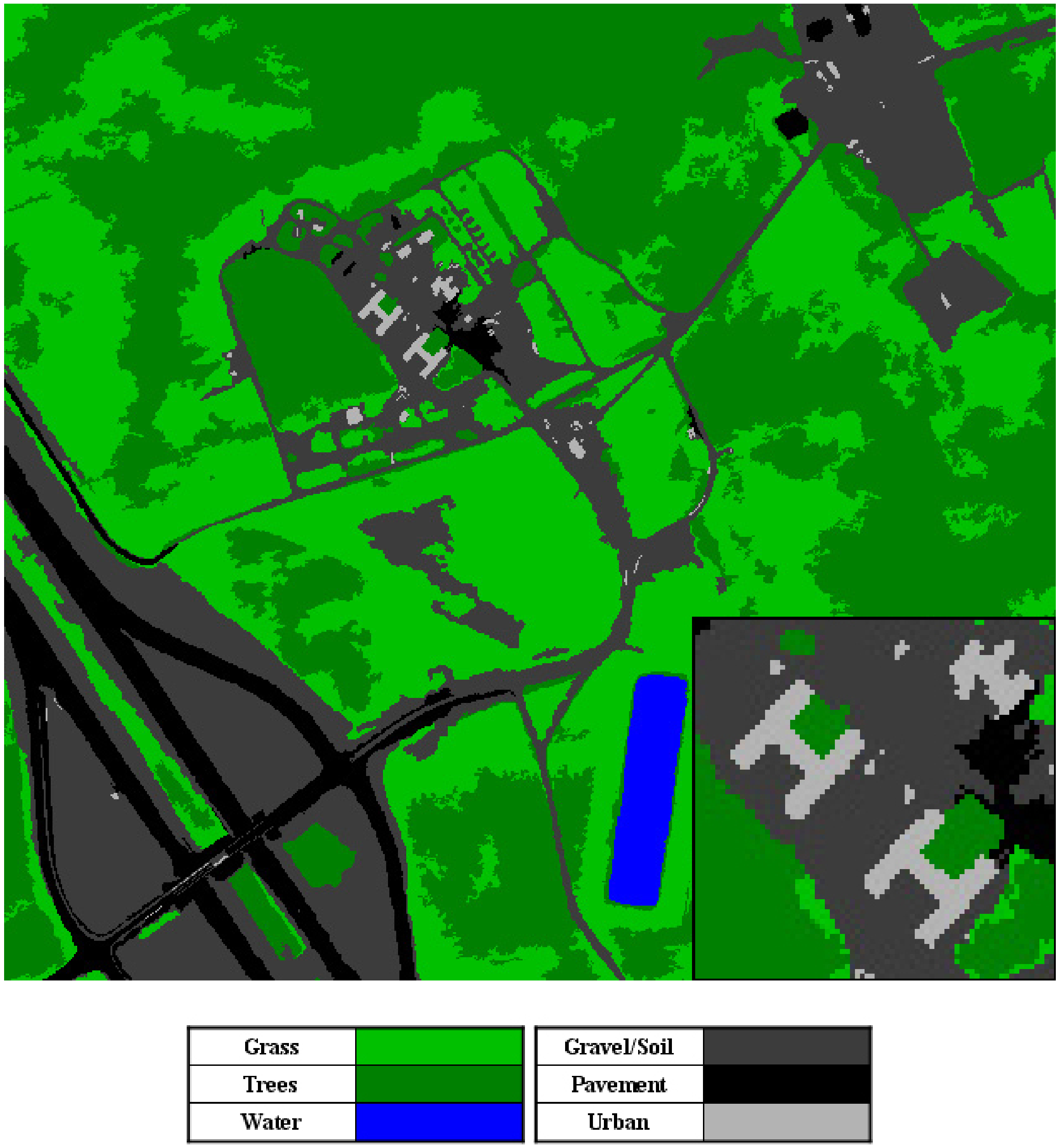


Figure 7.1
Rural scene classification using segmentation A (B, G, R, NIR layers)

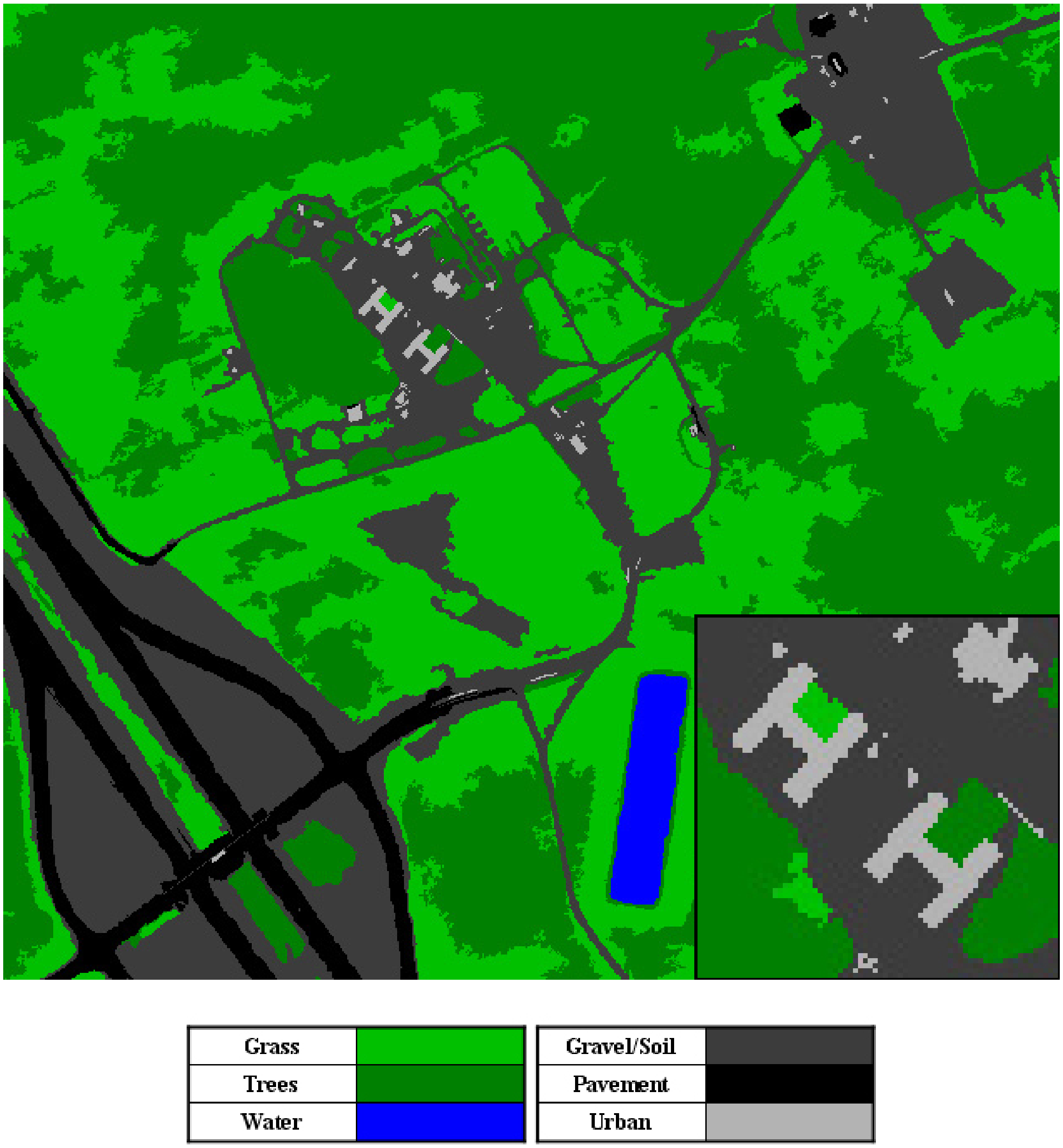


Figure 7.2
Rural scene classification using segmentation B (Pan, B, G, R, NIR layers)

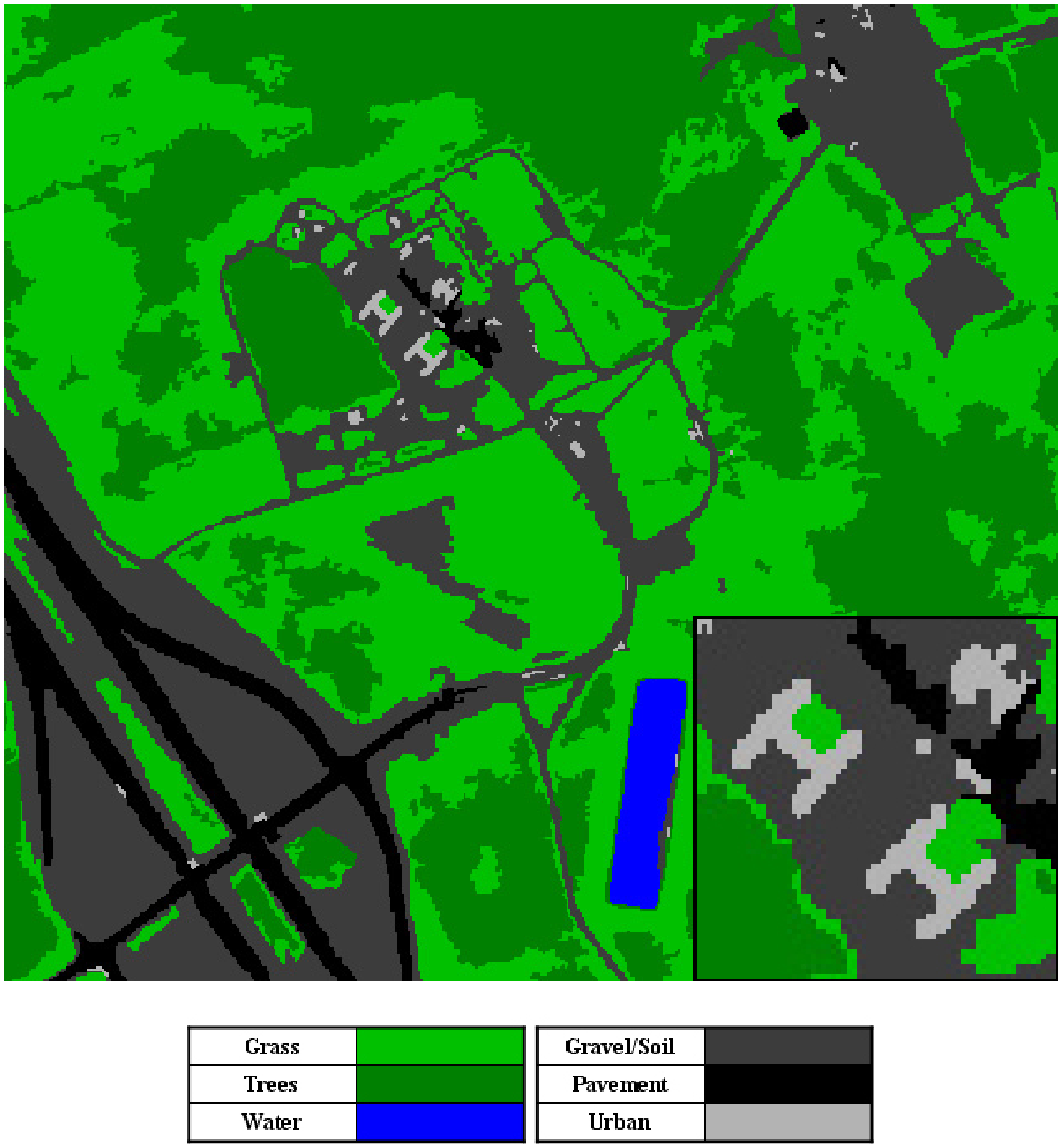


Figure 7.3
Rural scene classification using segmentation C (B, G, R, NIR layers)

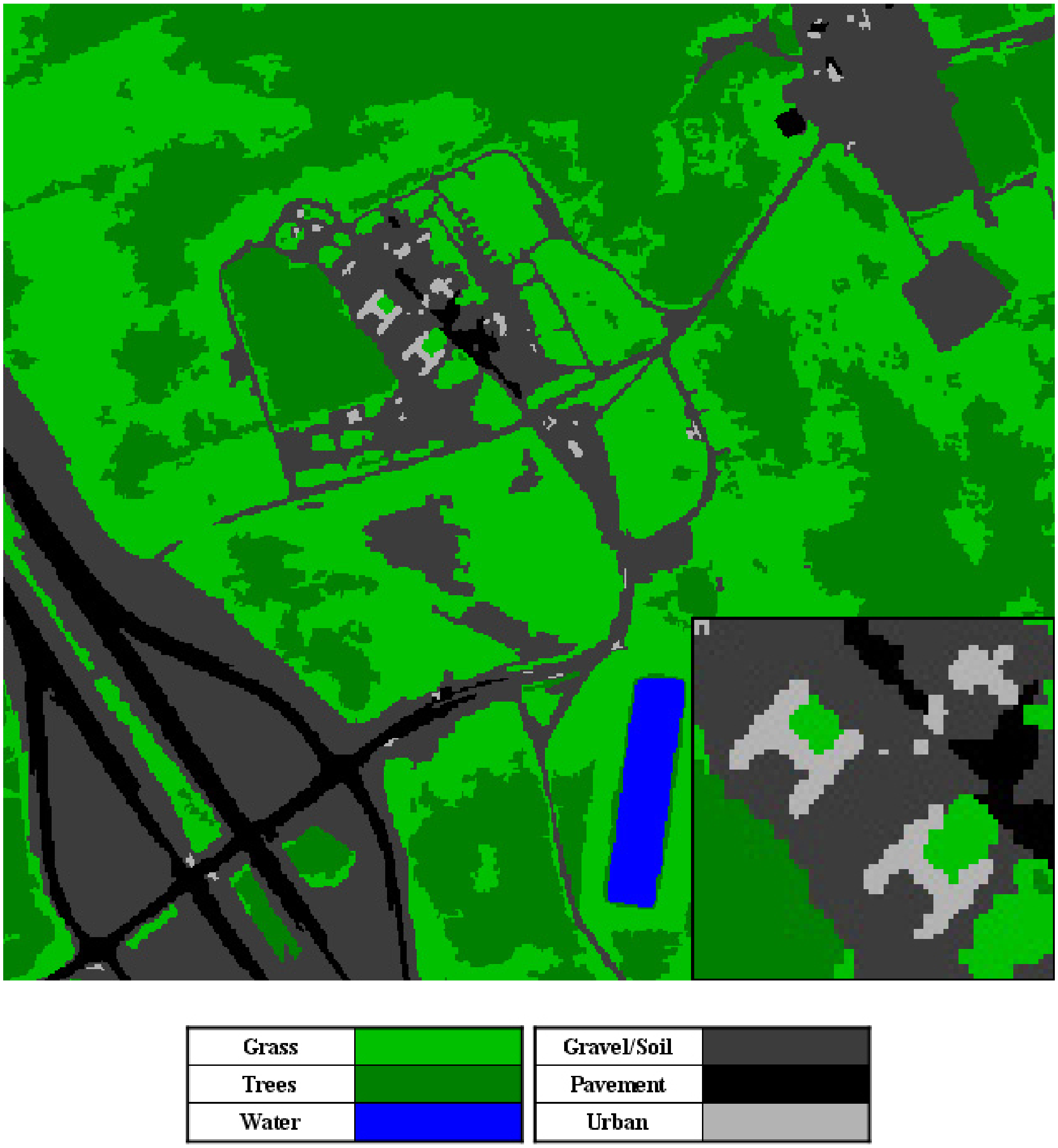


Figure 7.4
Rural scene classification using segmentation D (Pan, B, G, R, NIR layers)

Comparing the original and pan-sharpened classifications from the rural scene, we see that there is some noticeable improvement in border regions that is detectable. The pan-sharpened land cover classes are less pixilated and more representative of what we would expect to see. Visually more appealing, this difference is only apparent in the delineation of road and building features, whereas grass, trees, and water exhibit no significant improvement.

The effect of panchromatic channel inclusion in the segmentation routine reveals some interesting results. In the case of the original multispectral imagery, it appears that the panchromatic layer improves the segmentation of some features permitting a better classification. On the other hand, other features are oversegmented due to the increased texture of this channel and as a result, classification of these smaller segments is more easily confused. There appears to be no clear advantage for inclusion of the panchromatic channel in the multispectral rural imagery.

The panchromatic effects on the rural pansharpened imagery are more obvious. Since the panchromatic information is already incorporated into the fused imagery, the addition of the panchromatic channel into the segmentation routine seems to confuse objects more readily than using the pan-sharpened multispectral bands alone. This seems intuitively obvious and is demonstrated in the rural scene, particularly on buildings and roads where confusion in object delineation can be observed.

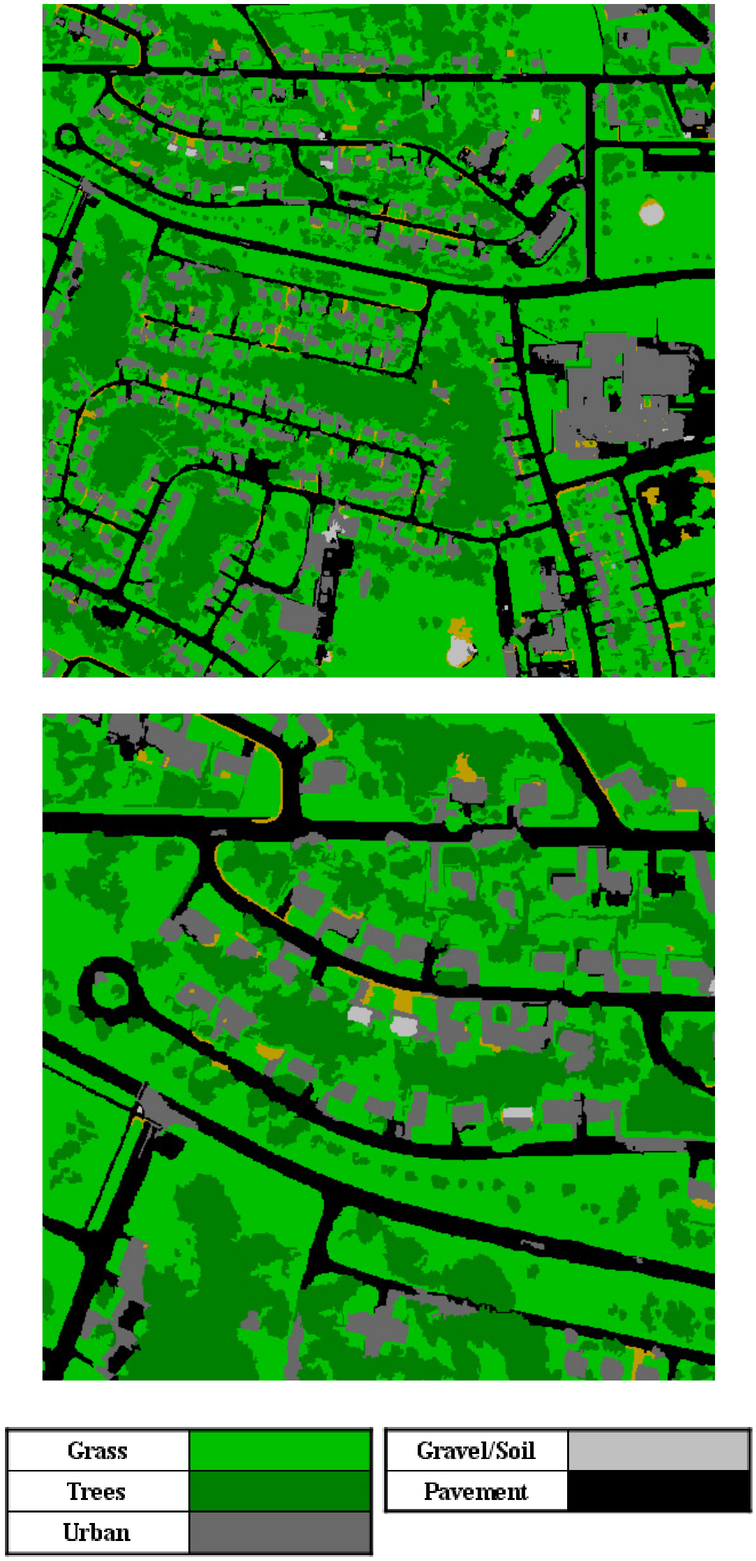


Figure 7.5
Suburban scene classification using segmentation A (B, G, R, NIR layers)

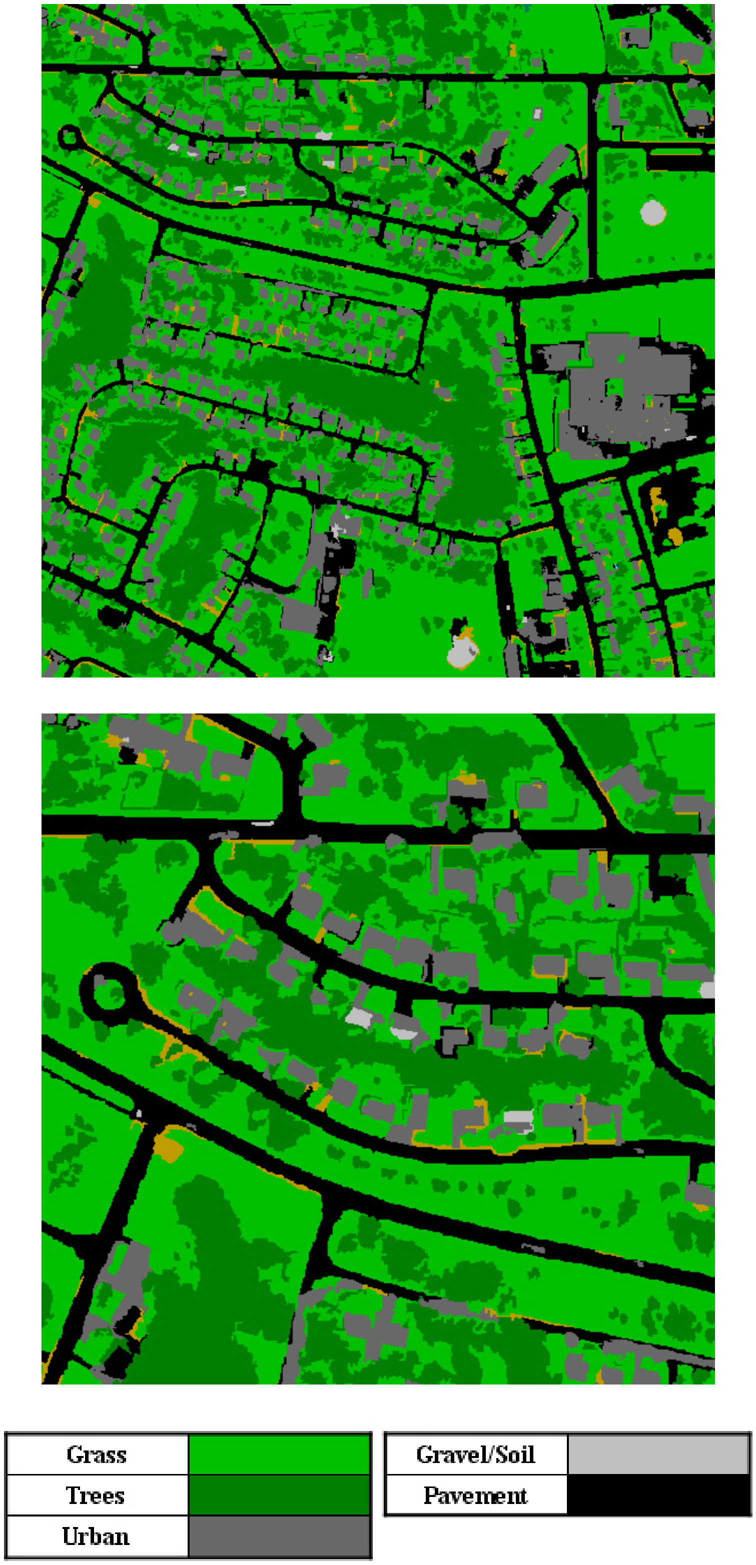


Figure 7.6
Suburban scene classification using segmentation B (Pan, B, G, R, NIR layers)

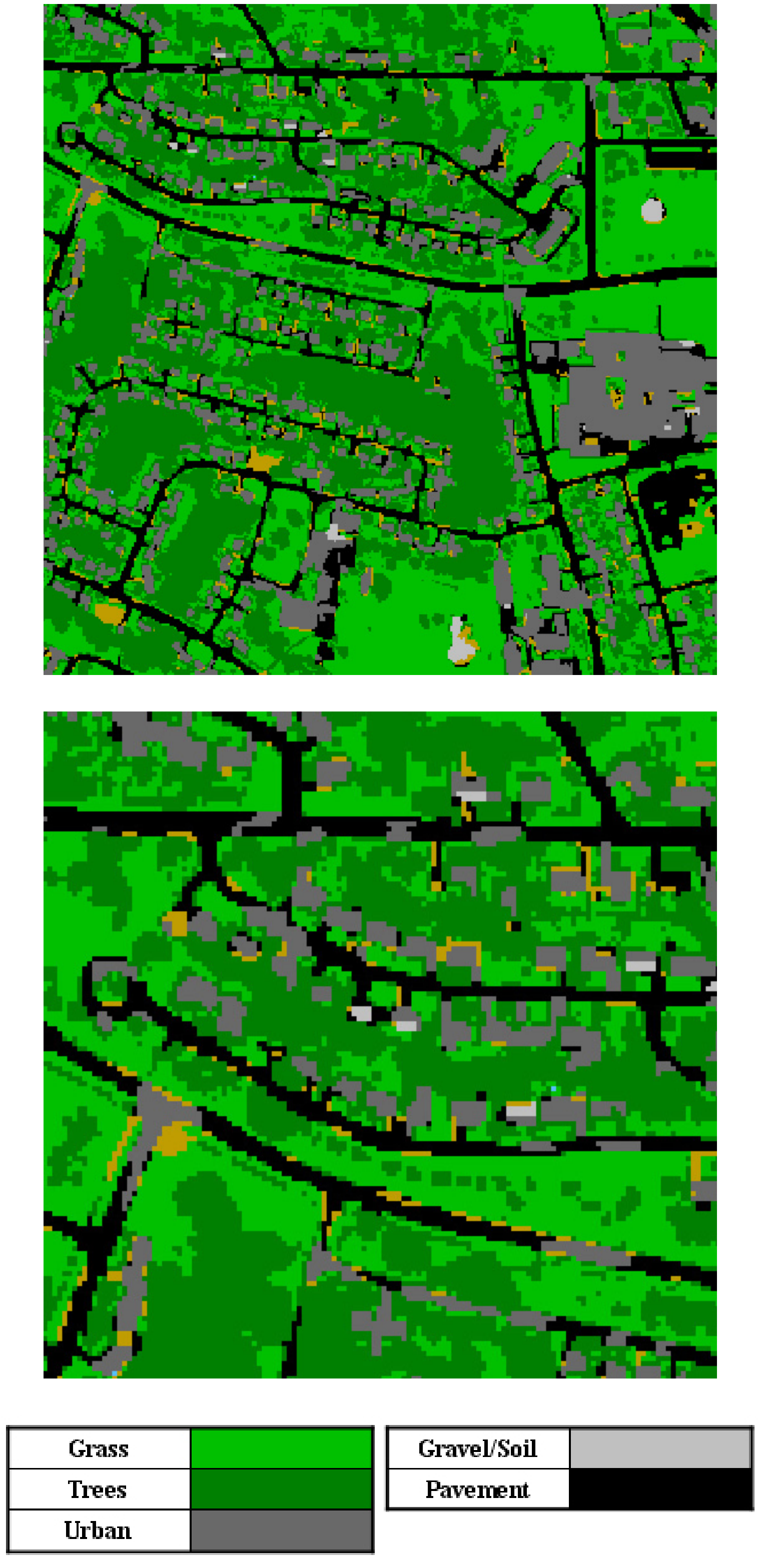


Figure 7.7
Suburban scene classification using segmentation C (B, G, R, NIR layers)

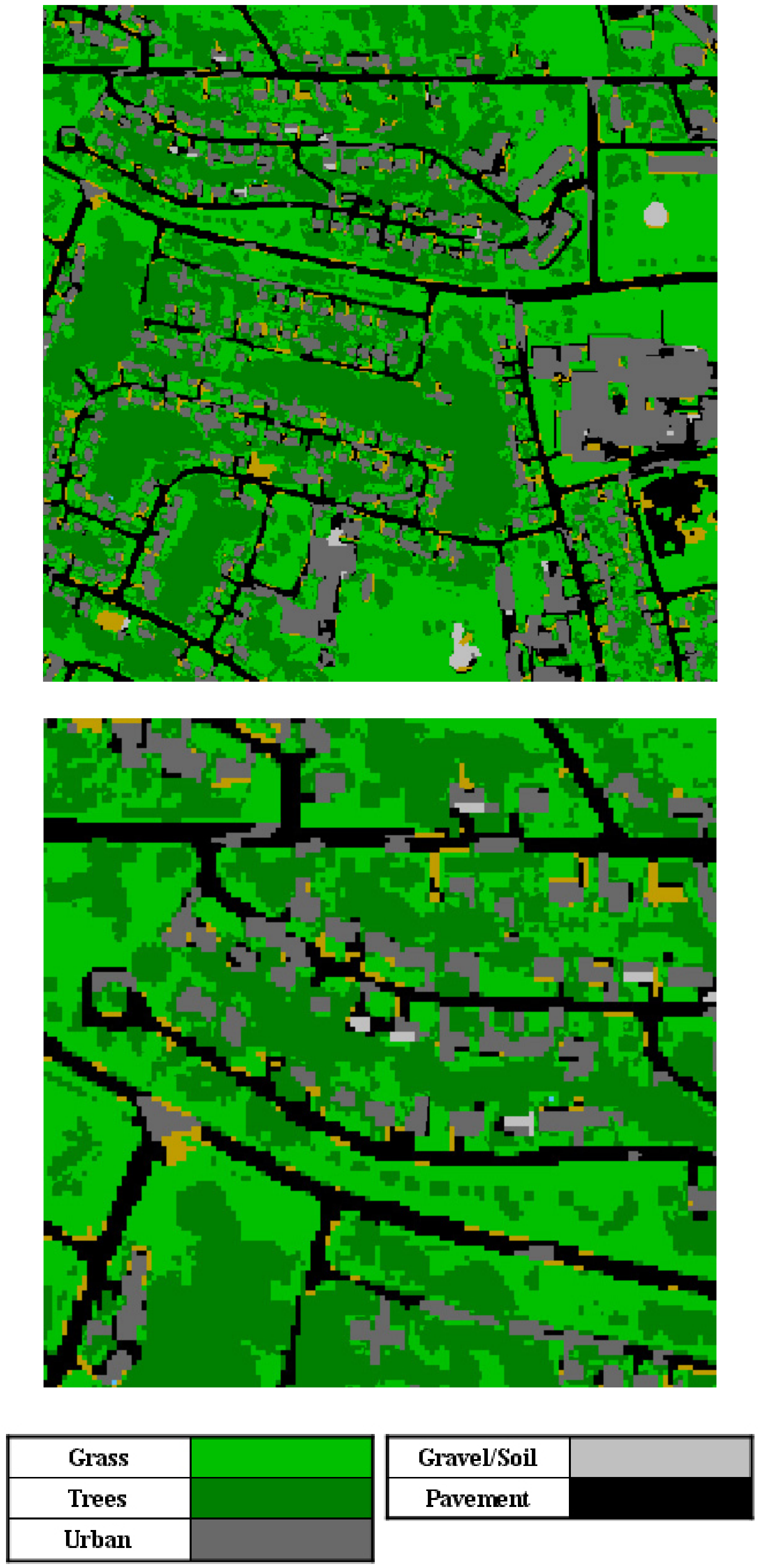


Figure 7.8
Suburban scene classification using segmentation D (Pan B, G, R, NIR layers)

Focussing our attention to the suburban classifications, we can see the most obvious visual improvement. In the case of the pan-sharpened imagery, the classifications display significantly improved detail over the original multispectral. The pan-sharpened classifications show better outlines for most land cover types, particularly in the case of roads, sidewalks, driveways, buildings, and lone trees. As a result of this improved detail, the shape and orientation of these features can be better established in the pan-sharpened classification. The use of the panchromatic channel in the segmentation demonstrates similar results to the rural scene, offering little benefit to the final result.

Overall, by means of visual assessment, the pan-sharpened imagery appears to offer a definite advantage. This demonstrates that eCognition is able to manage the higher texture of the pan-sharpened imagery and produce a visually superior result, particularly in the complex suburban environment. To get a true appreciation of the success and better establish a basis for comparison, it is necessary to statistically evaluate the results.

7.1.2 Statistical Assessment

7.1.2.1 Sampling Theory

To perform an accuracy assessment on a classification, it is necessary the classification contains *k* classes that are mutually exclusive and that the classification is totally exhaustive [Congalton and Green, 1999]. Mutual exclusivity ensures that each sampled element (pixel in our case) belongs to only one class. This requires a completely defuzzified classification, where each pixel belongs to the class with the highest membership value. A totally exhaustive classification requires that each pixel in the image is assigned a class, leaving no element unclassified. These criteria are met in our classifications.

With these prerequisites established, we turn our attention to determining the number of samples required and the method by which we will conduct the sampling. Assuming the case of a multinomial distribution of a finite population divided into *k* classes, the number of samples statistically required for a representative error matrix is described by [Congalton and Green, 1999]:

$$n = \frac{B(1-\prod_i)}{\prod_i b_i^2} \tag{7.1}$$

where *B* is the value of the Chi squared distribution at a specified confidence and one degree of freedom, $\prod_i$ is the proportion of class *i* relative to the population, and b_i is the precision of each class in the error matrix.

Balancing the statistical requirement for the number of samples is an element of practicality. Congalton and Green [1999] recommend that a minimum of 50 samples for each land cover type is reasonable and strikes a balance between statistical and practical requirements that has been confirmed by the above multinomial equation. This guideline was used to determine the number of samples taken in this research.

Finally, there are a number of sampling methods that can be employed to select the random samples from the imagery. These include: (1) simple random sampling; (2) systematic sampling; (3) stratified random sampling; (4) cluster sampling; and (5) stratified systematic unaligned sampling [Congalton and Green, 1999]. For this project simple random sampling and stratified random sampling were used. In simple random sampling, random pixel coordinates are selected and samples are taken from these points. Stratified random sampling is very similar except that the number of samples taken from each class is proportional to the size of that class in the classified image. This ensures that all classes are sampled regardless of how small they are. Selection of sampling method for each data set will be discussed in the next section.

7.1.2.2 Classification Accuracy Assessment

The rural scene was largely composed of tree and grass classes. Using either simple or stratified random sampling on this scene would create difficulties in sampling the very small urban and water classes. To better represent all the classes in the image, a subset (1.3km x 1.2km) of this imagery was used for classification accuracy assessment (Figures 7.1 through 7.4). The simple random sampling approach was selected since it managed to provide an improved sampling as compared to the stratified approach due to the small class size in for urban and water. A total of 400 samples were taken for each rural classification.

In the case of the suburban scene, all classes were better proportioned and as a result the accuracy assessment was conducted on the original size scene (3.2km x 2.6km). Once again, PCI Geomatica was employed using the stratified random sampling approach and taking a total of 450 samples. In both rural and suburban cases, the classified samples were compared to ground truth data as interpreted from a pan-sharpened image. The results for both scenes are consolidated in Tables 7.1 and 7.2.

Table 7.1
Classification accuracy assessment results for rural scene

Classification			Overall Accuracy	Kappa Statistic
Imagery		Segmentation Layers		
A	Pan-sharpened	Multispectral without Panchromatic	82.75%	0.741
B	Pan-sharpened	Multispectral with Panchromatic	84.25%	0.765
C	Multispectral	Multispectral without Panchromatic	86.00%	0.794
D	Multispectral	Multispectral with Panchromatic	83.75%	0.762

Table 7.2
Classification accuracy assessment results for suburban scene

Classification			Overall Accuracy	Kappa Statistic
Imagery		Segmentation Layers		
A	Pan-sharpened	Multispectral without Panchromatic	79.33%	0.723
B	Pan-sharpened	Multispectral with Panchromatic	79.95%	0.728
C	Multispectral	Multispectral without Panchromatic	81.11%	0.741
D	Multispectral	Multispectral with Panchromatic	79.33%	0.718

Overall these results indicate an average accuracy of about 84% for the rural scene and 80% for the suburban scene. More importantly than the absolute accuracies for this research, however, is the fact that the overall accuracies are similar within the same scene. There is no apparent distinction between the employment of multispectral and pan-sharpened imagery for the purpose of classification when using the object-oriented approach. Further, the accuracies seem to be independent of the use of the panchromatic image for segmentation.

To ensure that the overall accuracies are similar in a statistical sense, it is necessary to assess whether the differences between the overall accuracies are statistically significant. To address this issue Kappa analysis can be used [Congalton and Green, 1999]. The Z statistic is the result of Kappa analysis and is used to test whether two classifications are significantly different. The Z statistic for the comparison of two results is given by:

$$Z = \frac{\left|\hat{K}_1 - \hat{K}_2\right|}{\sqrt{\hat{\text{var}}(\hat{K}_1) + \hat{\text{var}}(\hat{K}_2)}} \tag{7.2}$$

where $\hat{K}_1$ and $\hat{K}_2$ are estimates of the Kappa statistic [Congalton and Green, 1999].

Using the Z statistic, the null hypothesis (that the results between two classifications are not significantly different) can be tested. In this manner, the relationships between all of the classification results were tested and are summarized in Tables 7.3 and 7.4.

Table 7.3
Z statistic results for rural classification

	Classification		
Classification	A	B	C
B	0.590		
C	1.369	0.775	
D	0.530	0.069	0.856

Table 7.4
Z statistic results for suburban classification

	Classification		
Classification	A	B	C
B	0.153		
C	0.514	0.361	
D	0.145	0.297	0.659

At a confidence of 95%, the null hypothesis is rejected if $Z \geq 1.96$. From a thorough examination of the Z Statistic results, we can conclude that there are no significant differences between the accuracies established in Tables 7.1 and 7.2.

7.1.3 Overall Assessment

The visual and statistical assessments of suburban and rural classifications seem to highlight a number of important points. For the purpose of clarity, the key results from these assessments are summarized in Table 7.5.

Table 7.5
Summary of results comparing pan-sharpened and original data sets for classification

Criteria	Multispectral Data	Pan-sharpened Data
Inclusion of Panchromatic channel for segmentation	No clear advantage	Achieves slightly better results without the panchromatic layer
Classification Accuracy	Statistically comparable	
Spectral Integrity	Original data	Maintained through least squares approach
Object Delineation	Delineation of grass, forest and water are comparable	
	Pixelated edges for roads and buildings	Obvious improvement in road and building edges
	Pixelated edges for small features	Improvement for small features such as lone trees
Shape	Small building shape is difficult to ascertain	Shape is significantly improved
	Less chance of success to classify based on shape features	May offer an advantage for classification using shape features
Orientation	Small building orientation difficult to determine	Able to determine orientation of small buildings very well

7.2 Segmentation Results using the Proposed Fuzzy Tool

7.2.1 General Segmentation Metrics

Zhang [1996] separates segmentation evaluation methods into three distinct categories: (1) analytical methods; (2) empirical goodness methods; and (3) empirical discrepancy methods. Analytical methods focus entirely on an evaluation of the algorithm itself. In our case, we are comparing the results of the same algorithm implemented with different parameters. Therefore, we are not interested in a direct evaluation of the segmentation algorithm, but instead, the results that are achieved. An empirical method is much more appropriate for our problem.

Empirical goodness methods are based on an assumption of the characteristics that form the perfect segmentation. These methods perform their evaluations based on these assumptions and have no requirement for a reference image. Although the lack of requirement for a reference image is an advantage of this approach, the generalizations made to characterize the ideal image are broad assumptions that may not be true in all cases. Some examples of proposed goodness measures are those based on intra-region uniformity, inter-region contrast, and region shape [Zhang, 1996].

Empirical discrepancy methods are those methods used to compare the resulting segmented image and a reference image. These methods provide a truly meaningful value representing how close the segmentation is to the proposed reference. Using this approach, a smaller discrepancy defines a better overall result [Zhang, 1996]. Figure 7.9 outlines where each of these evaluation methods are applied in the context of the segmentation workflow.

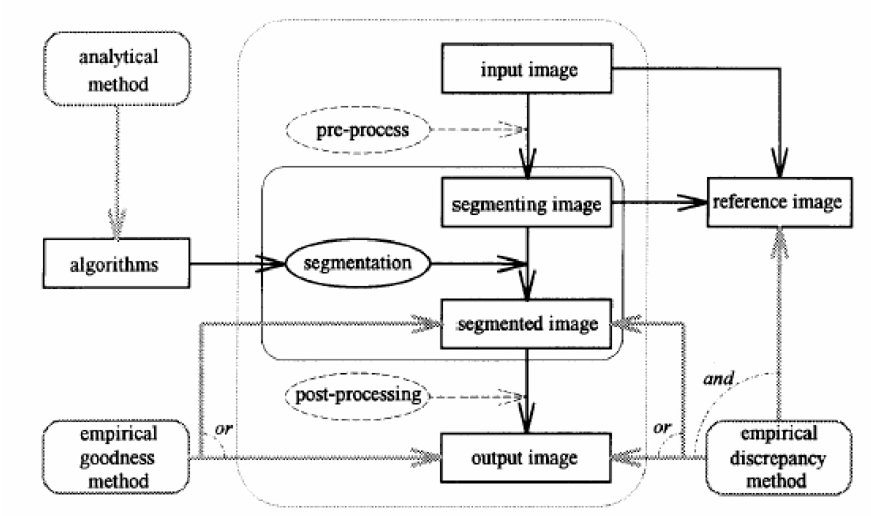


Figure 7.9
Evaluation methods in the segmentation workflow (from Zhang [1996, p. 1336]).

In addition to the above methods for evaluation, two others need be considered. First, the importance of a qualitative evaluation of the segmentation to ensure a visually convincing result should not be abandoned. After all, this is the sole evaluation method recommended by Definiens Imaging [2004b] for users of its application. Second, all of the previous measures have focussed on the segmentation result itself and have made no mention of the efficiency by which the segmentation can be executed. Since some algorithms may be executed more quickly and achieve comparable results, the evaluation must be a function of efficiency as well accuracy.

7.2.2 Segmentation Tool Assessment

The metrics outlined in Section 7.2.1 are all aimed at comparing different segmentation algorithms. In our case, we are using the same algorithm and are comparing the methods employed for parameter selection. In theory, the same segmentation is achievable using trial and error as that using the fuzzy tool approach. Therefore, a comparative assessment of the proposed fuzzy tool and recommended trial and error method should be based on: (1) empirical decision criteria; (2) qualitative assessment of results; and (3) efficiency. Each of these will be discussed over the next few sections.

7.2.2.1 Empirical Decision Criteria

Both methods employ a different set of decision criteria to select the best parameters for a specific segmentation level. The trial and error approach to parameter selection requires the user to observe a particular segmentation and mentally establish some measure of discrepancy between the desired segmentation and the actual segmentation. Using this information, the user proceeds transform this vague discrepancy measure into a set of new parameters, each of which is imprecise at best. To best learn how changes to the parameter values affect the resulting segmentation, one parameter is changed at a time. This approach is continued until a visually pleasing result is achieved, but qualitatively image segmentation almost always shows room for improvement. Thus, refinement of parameter selection is difficult to ascertain without some form of quantitative measurement by which to cease efforts to improve the result.

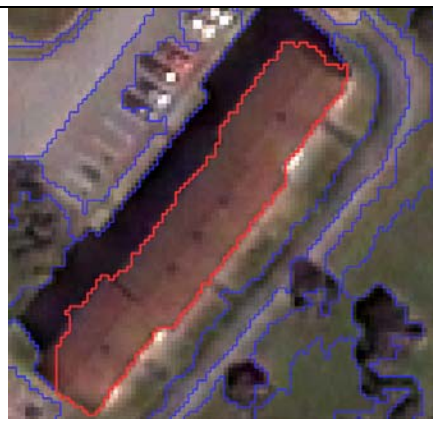
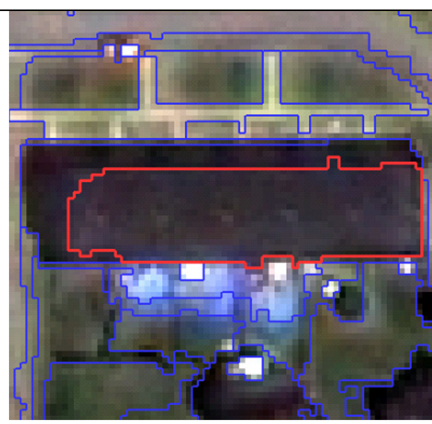
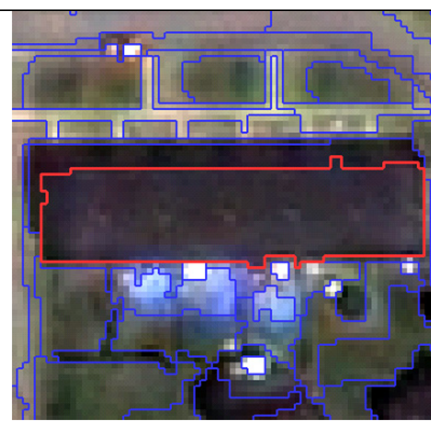
In contrast to this approach, the proposed fuzzy tool is built around the concept of empirical discrepancy evaluation. A number of discrepancy measures are used to guide the selection of the appropriate parameters. Many of the measures employed are object features that are internally compared to a supervised result. The comparison of object features in this manner is conceptually based on the Relative Ultimate Measurement Accuracy (RUMA) assessment methodology. This process has demonstrated the best ability to "precisely judge the quality of segmentation results" of all discrepancy measures. [Zhang, 1996; Zhang, 1997]. Consequently, convergence is evaluated based on size and scale features. If these discrepancy measures fall within the user defined convergence threshold, then parameter selection is ceased. Using this approach, the user can have confidence that the segmentation result meets a quantitatively derived standard without the need for further evaluation. The two approaches are compared in Table 7.6.

Table 7.6
Comparison of Decision Criteria

Criteria	Trial and Error	Proposed Fuzzy Tool
Evaluation of Segmentation	Qualitiative	Quantitative
	Based on result being "visually pleasing"	Based on feature comparison of result with the model object
Parameter Estimation	Mentally establish which parameters require adjustment	Uses key object features to determine which parameters require adjustment
	Based on experience and ability to make an "educated guess"	Based on measure feature values and estimated within a fuzzy inference system
	Vague approach requires changing one parameter at a time to establish effects	All parameters can be changed simultaneously using key feature values
Stopping Criteria	Result "looks good"	Based on discrepancy with the established model object

7.2.2.2 Assessment of Quality

Definiens Imaging [2004b] suggests that human perception is a powerful assessment tool by which to measure the success of segmentation results. Implementation of the fuzzy tool presented in this paper demonstrates very pleasing results that are convincing to human eye. For clarity, the results are compared once again in Figure 7.10.

Object	Trial and Error	Proposed Fuzzy Tool
Building with shadow		
Low contrast building with shadow		

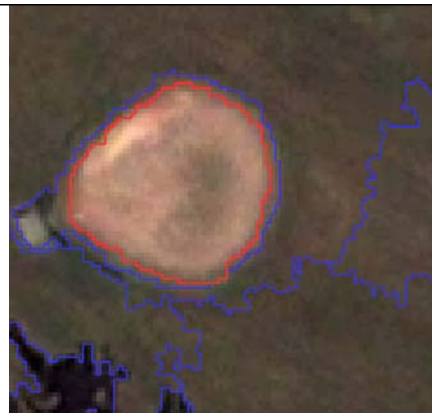
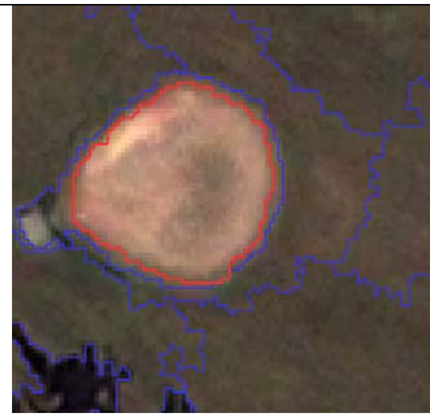
Ball diamond		
Lone trees		

Figure 7.10
Comparison of results between trial and error and proposed tool

Overall, these results demonstrate three important attributes. First, the sub-objects merge to a result very close to the desired solution. Once the user trains the system to extract an object of interest, the fuzzy methodology works very well to converge to the desired result. Second, the segmentation parameters selected by the fuzzy system work very well with eCognition’s distributed treatment order across the entire image. This produces well extracted objects across the image for land cover objects that carry similar properties to the final model object defined by the user. For example, a number of similar apartment buildings in a scene will all be extracted reasonably well, even when selecting only one as the sample object. Lastly, these results have demonstrated that the intermediate segmentations have a very important contribution to the final result. Starting with an initially oversegmented image, application of the final successful segmentation parameters determined by the fuzzy system may not result in a properly extracted object. The intermediate segmentation steps determined by the fuzzy tool are critical to the final segmentation success. These results are summarized in Table 7.7. Overall, the ability to determine important intermediate segmentations, to produce visually convincing results, and the applicability across the entire image demonstrates a high degree of success for this methodology.

Table 7.7
Comparison of segmentation results

Criteria	Trial and Error	Proposed Fuzzy Tool
Assessment of result (stopping criteria)	Qualitative	Quantitative
Applicability across image	May be compromised if spectral and shape parameters are not balanced	Designed to ensure appropriate parameter selection for applicability across image
Detail Retention	High degree of merging possible with inexperienced user	Extracts object of interest while minimizing object merging elsewhere
	May not be suitable for subsequent object extraction at a larger scale	Designed to retain detail and work as an initial segmentation for subsequent levels
Intermediate segmentations	Difficult to choose appropriate intermediate segmentations to ensure successful object extraction	Works with appropriate intermediate segmentations to ensure system will converge to final solution
Repeatability between users	Possible depending on parameters selected at each level	Possible depending on the initial segmentation and objects selected for training
Speed	Varies with user with software and data	Quick and automated with only simple training required

This methodology also has its challenges. To a large extent, the objects have been extracted in accordance with the direction of the user. Visually, however, some pixels may appear inappropriate for the object of interest. This often manifests itself on building edges where it causes them to be less than smooth, or on trees where the resulting shape is not completely as one would expect. These few pixels are a result of the initial segmentation state where pixels were grouped somewhat inappropriately for the task. These incorrect groupings were performed prior to initiating the fuzzy parameter selection tool as a result of the initial selection of parameters by the user. Although small in number, these incorrectly grouped pixels may be removed by performing the initial segmentation at a smaller scale. This will produce more objects and permit the user to select more appropriate sub-objects that even better represent the object of interest.

7.2.2.3 Efficiency

The objects in each case are extracted in accordance with the user's direction in an efficient and reliable manner. Efficiency is a measure of effectiveness without wasting time or effort. By this definition, the fuzzy tool demonstrates improved efficiency over the trial and error method by converging to a solution in relatively few iterations. The number of iterations required varies as a function of the land cover object being extracted and the initial segmentation state. However, in general the system converges in four iterations or less and is achieved by approaching parameter selection is a calculated and procedural manner instead of relying on intuition and experience as required using trial and error. In addition, the user does not have to evaluate the result after each selection of parameters since it converges near to the desired solution defined by the user in a fast and automatic manner. Training only once at the beginning of the session thereby saves additional time and contributes to the overall efficiency.

By the proposed method, there is no need for a time-consuming trial and error process which often forces the user to segment, assess results, delete results and segment again in an ongoing process until a convincing solution is achieved. Depending on the user's experience and understanding of underlying processes, the time taken to conduct this procedure may vary a great deal from one user to another. The advantages offered by the fuzzy tool are consolidated in Table 7.8.

Table 7.8
Comparison of method efficiency

Criteria	Trial and Error	Proposed Fuzzy Tool
Initial segmentation	Required	Required
Training	Not Required	Required
Evaluation of subsequent levels	Required by user after each iteration	Automated
Parameter estimation	Required by user after each iteration	Automated
Number of parameters changed per iteration	Only one recommended to see effect of selection	All parameters changed simultaneously
Number of iterations	Depends on user experience and object characteristics	Usually four iterations or less
Overall speed	Time-consuming	Quick
Simplicity	Difficult - especially for a new user or data set	Simple - suitable for the first time user with no experience

Chapter 8

Conclusions and Recommendations

Knowledge is a process of piling up facts; wisdom lies in their simplification.

[Martin Fischer]

8.1 Conclusions

The primary objectives for this research were: (1) to evaluate the capacity of object-oriented classification to manage VHR imagery, including a comparison of pan-sharpened and original multispectral images; and (2) to develop a supervised fuzzy approach to improve the efficiency of segmentation in the object-oriented classification workflow. Both objectives were successfully achieved.

8.1.1 Classification of UNB Pan-Sharpened Data

In the first case, the results achieved permit some important conclusions. Quantitatively, the classification of rural and suburban scenes using eCognition's object-oriented approach demonstrates that, in an absolute sense, the classification accuracies are very good with an average rural scene accuracy of 84% and an average suburban scene accuracy of 80%. The object-oriented approach was able to deal well with the low spectral and high spatial resolution characteristics of the VHR imagery and provide impressive results.

In a relative sense, the scene accuracies were independent of the imagery used. The significant increase in resolution did not improve or degrade the classification to any significant degree. This is an important conclusion for two reasons. First, eCognition was able to manage the higher texture of the pan-sharpened imagery and maintain quantitatively comparable results. By virtue of this result, it is obvious that the UNB Pan-Sharpening technique maintained the spectral characteristics of the original imagery to the degree necessary to make it a desirable alternative for the classification task when using the object-oriented approach. Second, the pan-sharpened classifications are visually more appealing than the lower resolution original classifications. This is especially true for urban classes and as a result, UNB Pan-Sharpened imagery should be used in complex terrain wherever possible when combined with the object-oriented classification approach.

The major difficulty encountered with the object-oriented approach using eCongition was the difficulty in selecting the appropriate segmentation parameters, particularly as a new user. This was identified as a major obstacle to the operationalization of this approach due to the time-consuming and inefficient nature of segmentation parameter selection. The identification of this problem directed this research into the development of a method to aid the user in establishing the best segmentation parameters for classification of specific land cover objects, with the emphasis on complex urban scenes.

8.1.2 Parameter Selection Tool

"Image segmentation is one of the most critical tasks in image analysis" [Zhang, 1996]. To date, eCognition's multiresolution segmentation approach has demonstrated a high degree of success in a number of applications using VHR satellite imagery. The non-intuitive nature of parameter selection in eCognition is the major drawback identified in this research to the otherwise successful implementation of the object-oriented approach.

In contrast to the suggested trial and error approach, the fuzzy segmentation parameter determination system proposed in this paper offers an important advantage over currently existing segmentation tools. The results are quantitatively convincing by employing a feature discrepancy test for convergence, qualitatively realistic through convergence to near the desired model object, and highly efficient as a result of convergence to a solution in relatively few iterations without the need for repetitive user interaction.

A drawback to the fuzzy approach is the possibility for a wide variety of different membership functions and rules which can be modified to improve the system. This provides a high degree of flexibility but comes at the cost of extensive testing to establish the optimal system. Consequently, these results only provide a basis from which to continue development of the proposed fuzzy tool. In the end, a successful parameter selection methodology will promote the automatization of the object-based approach to the classification of land cover. This remains a worthy objective given the promise of the object-oriented approach and the continuing trends in satellite sensor technology.

8.2 Recommendations

It is reasonable to expect that UNB Pan-Sharpened imagery may yet offer a further classification benefit by taking full advantage of shape in the classification hierarchy. In this way, the absolute accuracies of each pan-sharpened classified scene may be improved if a better overall segmentation could be achieved. Balanced with this requirement, however, is the practical necessity for the segmentation to be completed in a time efficient manner.

In this context, further research should be conducted on other scenes and a wider variety of land cover objects to determine the reliability and robustness of the proposed system. Working towards this goal, features, rules and membership functions could continue to be modified in an effort to optimize the system. To confirm the optimization of the system, other empirical methods for segmentation evaluation such as those proposed by Zhang [1996] could be applied to determine additional quantitative measures of segmentation success. These measures could be further confirmed through a comparison of classification accuracies resulting from employing the proposed system and the results achieved through trial and error. This comparison would best be carried out by permitting the same amount of time for segmentation using each approach. This would provide a quantitative measure of the efficiency of the proposed system compared to trial and error.

Furthermore, testing the fuzzy tool to extract successive levels should be carried out. This would involve using previous level segmentations as the starting point to extract other larger scale objects. Alternatively, the largest objects could be extracted first followed by successive segmentations using the initial oversegmented image. In this way, the best methodology for this tool could be determined to establish a complete object hierarchy. With additional research and more results on a wider variety of scenes, we may truly see the advantage of this technique when incorporated into the object-oriented image analysis workflow.

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