TOWARDS IMPROVING SEGMENTATION OF VERY HIGH RESOLUTION SATELLITE IMAGERY

BEN A. WUEST

September 2008

GEODESY AND GEOMATICS ENGINEERING
UNB

TECHNICAL REPORT
NO. 261

TOWARDS IMPROVING SEGMENTATION OF VERY HIGH RESOLUTON SATELLITE IMAGERY

Ben A. Wuest

Department of Geodesy and Geomatics Engineering
University of New Brunswick
P.O. Box 4400
Fredericton, N.B.
Canada
E3B 5A3

September 2008

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 2008. The research was supervised by Dr. Yun Zhang, and support was provided by the Natural Sciences and Engineering Research Council of Canada.

 The citation to this work should appear as follows:

Wuest, Ben A. (2008). *Towards Improving Segmentation of Very High Resolution Satellite Imagery*. M.Sc.E. thesis, Department of Geodesy and Geomatics Engineering Technical Report No. 261, University of New Brunswick, Fredericton, New Brunswick, Canada, 123 pp.

"Once in a while you get shown the light in the strangest of places if you look at it right."

Robert C. Hunter

DEDICATION

This thesis is dedicated to Randy Cable. You are with me every day my fallen friend.

ABSTRACT

High resolution satellite sensors, like QuickBird, have increased the dynamic grey-value variety and spatial detail in satellite imagery. New features can be distinguished that could not be discriminated in lower resolution imagery, such as that of Landsat TM. Object-oriented classification has shown significant promise as a method for the analysis and classification of objects in very high resolution imagery. This approach allows researchers to analyze pixel groups rather than individual pixels. Consequently, other features, such as texture and shape, can be applied to analysis. Object-oriented classification, however, is highly dependent upon successful image segmentation.

This research proposes to investigate segmentation methods -- through algorithmic approaches -- for the purpose of reducing operator dependency, fragmentation, parameter complexity and improving other segmentation problems and restrictions. This research is conducted over a variety of high resolution satellite image scenes. The focus of this research will be region-based, unsupervised segmentation methods on very high resolution satellite imagery.

ACKNOWLEDGEMENTS

I would primarily like to thank Dr. Yun Zhang and Dr. David Coleman for providing me with the opportunity to conduct this research. Without their support, this research would not have been possible. In addition, I would like to thank Dr. Yun Zhang for supervising and providing me with research funding (NSERC Discovery) and proper guidance to complete the research and this thesis.

I would like to thank the City of Fredericton and DigitalGlobe® for providing the data used in this research. The wide variety of data was essential to this study.

Thanks are given to the staff at the GGE Department and to my colleagues that were around me at UNB. The study environment and supporting staff was excellent and I will cherish the friendships I have made in this faculty for a long time.

I would also like to thank my parents, Lawrence and Judy Wuest for their consultation and support during the completion of this thesis. Their words of wisdom were essential in crunch times.

Last, but not least, I would like to thank my partner Michelle White for her support. I appreciate the proofreading and the advice. We spent many days side by side in our office working on our respective theses. If we can get through that we can get through anything.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AR	Area Ratio
ART	Adaptive Resonance Theory
B	Blue
BP	Boundary Pixel
CD	Common Density
DD	Density Dissimilarity
DN	Digital Number
FL	Fuzzy Logic
FBR	Fuzzy Band Ratio
G	Green
HSMR	Hierarchical Split Merge Refinement
MFC	Microsoft Foundation Classes
MI	Merge Importance
MS	Multispectral
MSC	Merge Stop Condition
NIR	Near Infra-Red
OO	Object Oriented
R	Red
RSI	Remote Sensing Images
SM	Similarity Measure
St. Dev	Standard Deviation
TIFF	Tagged Image File Format
VHR	Very High Resolution

CHAPTER 1

INTRODUCTION

Presented is the development of segmentation methods for very high resolution (VHR) satellite imagery. These methods incorporate segmentation theories, remote sensing principles, fuzzy logic and object oriented programming. This body of work is presented through the following papers which comprise this thesis:

Paper 1 (peer reviewed):

Wuest, B., and Y. Zhang (2008). "Region Based Segmentation of QuickBird Multispectral Imagery through Band Ratios and Fuzzy Comparison." *ISPRS Journal of Photogrammetry and Remote Sensing,* (Accepted for publication, July, 2008)

Paper 2 (peer reviewed):

Wuest, B., and Y. Zhang (2008). "Region Based Segmentation of QuickBird Multispectral Imagery through Fuzzy Integration." Proceedings of the *ISPRS XXI Congress*, Beijing, China, 3-11 July, pp. 491-496.

Paper 3 (peer reviewed):

Wuest, B., and Y. Zhang (2008). "Supervised Region Based Segmentation of QuickBird Multispectral Imagery" Proceedings of the *2008 IEEE International Geoscience & Remote Sensing Symposium (IGARSS 2008),* Boston, USA, 6-11 July.

The subsequent chapter will bridge together the above publications using the following approach by including the following:

1. An outline of the structure of the article-based thesis;

2. A background discussion of satellite imagery;
3. The definition of image segmentation along with descriptions of key existing approaches;
4. A discussion of the importance of this research;
5. Identification of segmentation problems and restrictions;
6. A description of Research Objectives;
7. Proposed strategies to reach these Objectives; and
8. A brief overview of the publications in this thesis.

1.1 Thesis Structure

For all of the publications presented in this thesis, the first author conducted the primary research while the second author provided advice on structure and content. The software design for this research is included in Appendix I. The structure of this thesis is presented in Table 1.1. In addition to the information provided in this chapter, bridging chapters have been included between publications for further clarification.

Table 1.1: Thesis Structure

Chapter	Content
1	Introduction
2	Paper 1
3	Bridging between Paper 1 and 2
4	Paper 2
5	Bridging between Paper 2 and 3
6	Paper 3
7	Conclusions
8	Appendices

1.2 Background

With the upcoming launch of the GeoEye-1 satellite, remote sensing imagery (RSI) will achieve another advance in spatial resolution. The proposed spatial resolution of GeoEye-1 is to be as high as 0.41 m on the Panchromatic Band and, more importantly, 1.65 m on the Multi-Spectral (MS) bands of red (R), green (G), blue (B) and near infrared (NIR). This launch will surpass the current spatial resolution held by DigitalGlobe's QuickBird satellite since 2001 which has offered 61 cm – 71 cm on the Panchromatic Band and 2.44 – 2.88m on the MS bands. QuickBird imagery has been the standard for very high resolution (VHR) satellite imagery for the last five years and been subject to numerous research endeavors [Hu et al., 2005; Hagner and Reese 2007; Mallinis et al., 2008].

VHR resolution imagery is unique because of its spatial resolution properties. The high spatial resolution gives operators the ability to map earth surface areas at a new level. Older satellite imagery, such as that provided by Landsat TM, does not provide capabilities to this extent. This is illustrated in Figure 1.1, which shows the considerable difference between low and high resolution satellite imagery. Some characteristics of VHR imagery include:

1. The increased spatial detail that leads to highly textured areas;
2. Spatial feature representation which causes linear objects to be represented by complex polygons; and
3. The presence of small objects such as houses and vehicles.

[a] [b]

Figure 1.1: Spatial detail from low and high resolution sensors (512x512 images). [a] Landsat TM 30m MS and [b] QuickBird 2.44m MS.

These characteristics are some of the areas that have been the subject of research investigations since the release of the QuickBird satellite in 2001. Pixel-based classifications methods have been successful within lower resolution satellite imagery such as that from Landsat ™. These methods are based upon statistical measurements of individual pixel digital number (DN) values. and are implemented using mechanisms such as Maximum Likelihood and the ISODATA clustering algorithm. For example, Hagner et al. [2007] produced a successful forest type classification approach using a calibrated Maximum Likelihood method. A comparison of Maximum Likelihood and ISODATA to Linear Spectral Mixture Modeling (LSMM) on Landsat TM data is presented by Shanmugam et al. [2006] in their study on classifying wetland characteristics. These methods, however, seldom take into account the full use of land cover characteristics such as shapes, structure information and spatial distribution in very high resolution satellite imagery [Liu et al., 2006]. In response to the birth of VHR imagery, academic and private sector research endeavors have turned to the object oriented paradigm.

Object oriented (OO) classification asserts that regions/segments of an image are classified rather than individual pixels. In this method, topology information in an image can be analyzed. Groups of pixels, rather than individual pixels, are analyzed. This provides the ability to include shape and complex texture measurements in image analysis rather than individual pixel statistics. Figure 1.2 provides a visual representation of the advancement in attribute selection provided by OO classification techniques. Figure 1.2a shows an object outlined in orange which can be described by shape, spectral and textural measurements. It can also be related to other objects that exist in its proximity. Figure 1.2b displays one pixel that can have statistics measure on it based on a localized window.

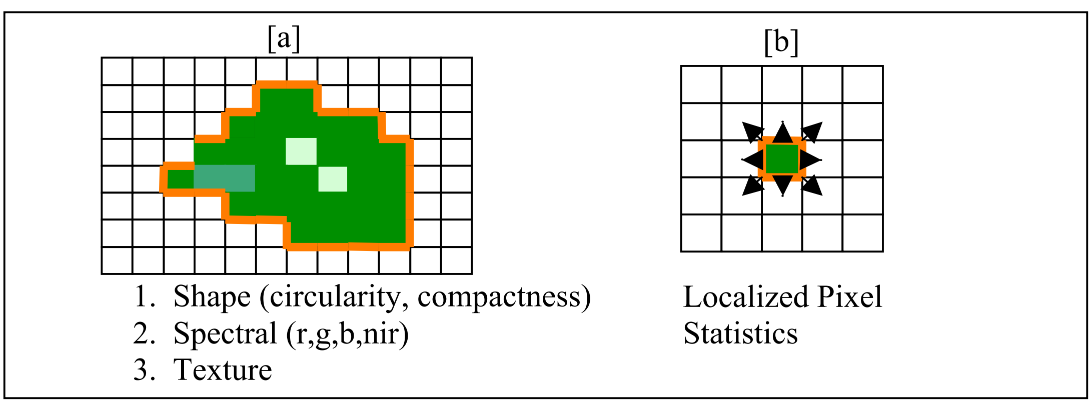

Figure 1.2: Difference between Object Based and Pixel Based Measurements. [a] Object Based representation and [b] Pixel Based representation.

The OO approach increases the analytical ability of classification algorithms to classify objects within an image. As stated by Maxwell and Zhang [2006], there are generally two steps needed in object-oriented classification: (1) segmentation, and (2) classification. Objects cannot be classified if they are not isolated as segments from within a given image. Image segmentation is the mechanism in which an image is partitioned into homogeneous segments and directly affects the accuracy of analytical results.

1.2 Definition of Segmentation

Image segmentation is the partitioning of an image into related sections or regions [Tilton, 2003]. Segmentation has existed for years in pattern recognition fields. For technical details of traditional segmentation techniques, readers can refer to Pal and Pal [2003]. From an algorithmic perspective, image segmentation is generally divided into four categories [Schiewe, 2002]:

1. Point-based;
2. Edge-based;
3. Region-based; and
4. Hybrid/Combined

1.2.1 Point-based

Point-based segmentation methods are generally performed by applying a global threshold(s) on individual pixels within an image. Thresholds categorize a pixel into two or more clusters according to the given threshold function. The choice of a threshold can be quite difficult in VHR imagery due to the dynamic variety of spectral information. Figure 1.3a shows a point based segmentation of the image in Figure 1.1b using thresholds based on known band ratios in remote sensing.

1.2.2 Edge-based

Edge-based methods attempt to use an edge detection filter to obtain the edges/contours of segments in a given image. The tracing of these contours can be quite complex and, as Figure 3b indicates, the contours can be broken and incomplete. This method is generally not applied to VHR imagery because of its complex features.

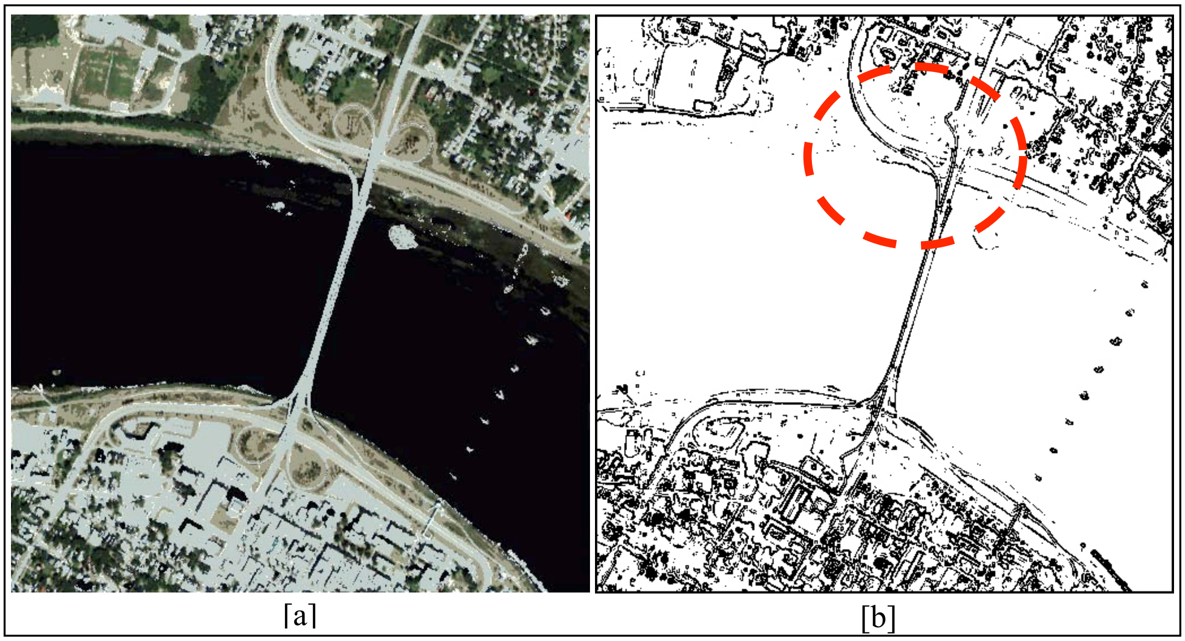

Figure 1.3: Results of point-based segmentation and contour tracing of QuickBird 2.44m MS Imagery. [a] Point based segmentation [b] Sobel contour tracing.

1.3.3 Region-based

Region-based methods are either performed by either a) Growing regions from individual pixels or b) Splitting the image into individual sets of pixels and merging them back together. Region growing involves growing pixels from one pixel in the image until certain specified threshold or conditions are met. Split-Merge procedures involve splitting the image into smaller segments and then grouping them back together, according to specified measures of homogeneity. Tilton [2003] offers an analysis of hierarchically related segmentations building on work presented by Beaulieu and Goldberg [1989].

Region based methods are the most popular method of VHR image segmentation. They are the foundation of the Fractal Net Evolution Approach (FNEA) developed for Definiens' *eCognition*™ software (currently the most advanced commercial software for OO classification). A detailed explanation of this approach can be found in Baatz and Scape [2002].

1.3 Importance of Segmentation

Segmentation, as indicated earlier, is a necessary precursor to object-based classification. The classification of objects can only be successful if the segmentation of the image is successful. Geo-related applications for fields such as forestry, mapping, change detection and agriculture are depending more and more on segmentation for information extraction. It is not practical for this process to be performed manually. The amount of satellite imagery for most applications renders manual segmentation inefficient in that it is very time consuming.

Segmentation, is therefore, directly significant to many applications in remote sensing such as urban planning, agriculture, land use mapping, and forestry. In forestry, Wang and Boesch [2007] demonstrate the results of segmentation on a key-issue of Forest delineation. This is very important in aerial image interpretation. Hu et al. [2005] demonstrate the success of image segmentation on the segmentation of land coverage areas. This type of segmentation is important to urban planning because land cover features can be cross referenced with census and other population related data.

1.4 Problems and Restrictions

This section presents some of the primary problems and restrictions in the segmentation of VHR imagery. These are issues that require attention in the search for automatic segmentation techniques. There are five designated points:

1. Parameter Complexity;
2. Operator Dependency;
3. Consistency of Results;
4. Fragmentation; and
5. Time Complexity

1.5.1 Parameter Complexity

Most VHR image segmentation solutions are accompanied by a set of parameters. In some cases these parameters can be quite complex and the number of parameters can be large. The process by which parameters are chosen can at times be a process of trial and error. As indicated in Moller et al, [2006], the wide range of variables to manipulate for segmentation can provide the user with drastically different results. In that article, the authors demonstrate a method to evaluate segmentations to resolve an optimal segmentation and thus reduce parameter complexity for the user. Maxwell and Zhang [2006] introduced research for dynamically estimating parameters on a localized basis. Both of the above papers are examples of research into how to reduce the parameter complexity of segmentation. This is a major challenge in the segmentation of VHR satellite imagery.

1.5.2 Operator Dependency

Operator dependency is directly related to other issues in segmentation such as parameter complexity. Segmentation is generally more successful if the operator has previous experience with the imagery. If the user is familiar with the segmentation system and parameters used to obtain proper segmentation results, the process can be less time consuming and produce desirable segmentations. To reduce this dependency, segmentation must be more automatic and not be dependent on the prior knowledge of the operator.

1.5.3 Consistency of Results

One of the most serious problems in the segmentation of VHR imagery is the consistency of results from one scene to the next. An algorithm may work on one image scene and be completely inaccurate on the next. Parameters set for one scene may have drastically different effects when applied to another scene. This is shown in Figure 1.4 in an HSMR segmentation of two different urban scenes for land coverage. Figure 1.4a shows the successful segmentation of a Boston suburban scene, while Figure 1.4b shows unsuccessful segmentation (over segmentation) as the same algorithm has problems segmenting the river from the other land coverage segments.

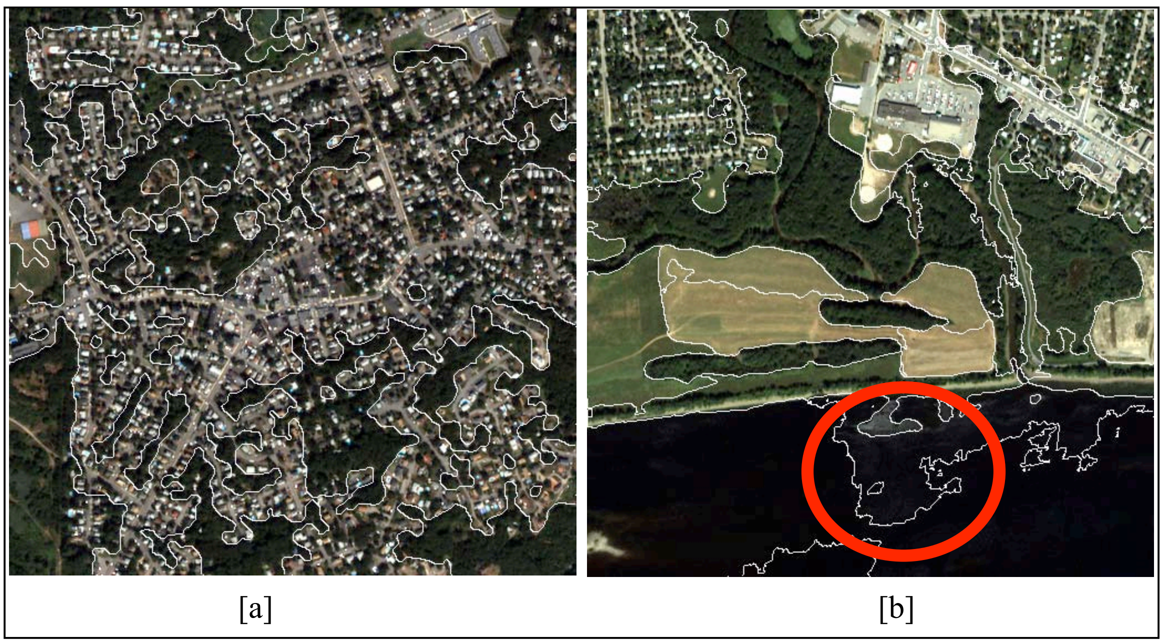

Figure 1.4: Example of segmentation inconsistency using the same segmentation methodology with a static set of parameters. [a] successful segmentation of land coverage in a suburban Boston, USA scene, and [b] unsuccessful (over) segmentation of land coverage in the city of Fredericton, NB Canada.

1.5.4 Fragmentation

Fragmentation is a key problem that exists in VHR image segmentation. Artifacts or small pieces of information can be leftover from segmentation. Fragmentation can also cause undesirable holes in regions. This problem exists more predominately in some solutions than in others and can cause difficulties for successful classification. Examples of fragmentation are shown in Figure 1.5.

Figure 1.5: Fragmentation in segmentation of VHR satellite imagery.

1.5.5 Time Complexity

The performance of segmentation algorithms depends on the characteristics of the image under investigation [NG et al., 1996]. As indicated previously there is incredible amount of spatial detail in VHR imagery which leads to complex textures. There have been a variety of texture measurements proposed in digital image processing and each measurement has a tradeoff between performance and feature discrimination. Ojala and

Pietikainen [1996] proposed a computationally efficient texture measure using local binary patterns. Texture can also be measured using entropy measures defined by Shannon and Weaver [1949]. Entropy and other measures like Grey Level Co-Occurrence Matrices (see Parker [1996]) can provide efficient results but are computationally costly. The choice and definition of texture is a major subject of research in image segmentation and, as indicated, can have effects on the computational complexity of the algorithm. Chen et al [2006] provide and in-depth discussion on reducing the computational complexity for texture based segmentations.

In addition, the time complexity of any given segmentation algorithm can be affected by mechanisms incorporated into the segmentation algorithm itself. Whether these mechanisms are Neural Networks, Fuzzy Logic, Least Squares, or any other type of approach, they may introduce some time concerns into the algorithm. A balance must be found according to the image content. These mechanisms sometimes have their own set of parameters which can introduce more time complexity into the segmentation algorithm. Fan et al [2008] detail the effects of a Support Vector Machine (SVM) on the segmentation of bacteria images.

Finally, the size of an image can have effect of the time it takes to computationally process an image. Given the bit depth of VHR imagery, the size of images can become quite large. Depending on the machine, this can become quite cumbersome for any segmentation algorithm or application.

1.6 Objectives

The research goal of this research is to improve the segmentation of Very High Resolution (VHR) satellite imagery by addressing issues (consistency, fragmentation, etc.) outlined in section 1.5. This HSMR framework for unsupervised segmentation is the basis for all of this research and the subject of improvement. For this goal, a number of supporting objectives are identified:

a. Create a method of a) reducing fragmentation; and b) improving consistency in the unsupervised HSMR segmentation approach;
b. Create new methods of region description and region comparison that improve consistency, user dependency and time performance in the unsupervised HSMR framework; and
c. Create a supervised HSMR segmentation algorithm that improves consistency and reduces parameter complexity.

1.7 Methodology

This section outlines the research that will be performed to meet the outlined objectives. This research will be performed on QuickBird 2.44m MS imagery. All algorithmic processes will be implemented using C++ programming language. The five primary sections of the research are outlined as follows:

a. Review and implement the existing HSMR unsupervised image segmentation solution;

b. Propose and implement methods for improving sections of the algorithm with regard to consistency and fragmentation;

c. Propose and implement new methods of region description and comparison through Band Ratio development and Fuzzy Integration;

d. Design and implement a supervised version of the HSMR algorithm; and

e. Evaluate results.

1.7.1 Review of Existing Solution

For the purpose of understanding the limitations and restrictions of existing segmentation solutions, a version of the Hierarchical Split Merge Refinement (HSMR) framework for unsupervised segmentation will be implemented and tested. There have been different implementations of the HSMR algorithmic framework for unsupervised region-based segmentation. It was first introduced by Ojala and Pietikainen [1999] in their study of texture based segmentation. It has been employed by Chen and Chen [2002] and more recently Hu et al. [2005] in the field of remote sensing. In this task, the adaptive algorithm presented by Hu et al. [2005] will be implemented. This adaptive algorithm has proven to be successful in the segmentation of land coverage categories.

1.7.2 Improvement of Existing Solution

From the experience obtained in reviewing an implementation of the HSMR framework, two tasks will be performed:

a. Revise the HSMR algorithm to improve the fragmentation in segmentation results; and

b. Revise the HSMR algorithm to improve the consistency of segmentation results.

1.7.3 New HSMR Solutions

Using Fuzzy Logic as a basis for region comparison, two new HSMR solutions will be produced. The first will use band ratios to introduce a certain prior knowledge to image segmentation. It is hypothesized that this process will produce consistent land coverage segmentation results. In the second implementation, the band ratio class development will be replaced by Fuzzy-ART. In this version, certain knowledge will be obtained, dynamically, from the Fuzzy-ART clustering mechanism. Figure 1.6 details an overview of these two new solutions.

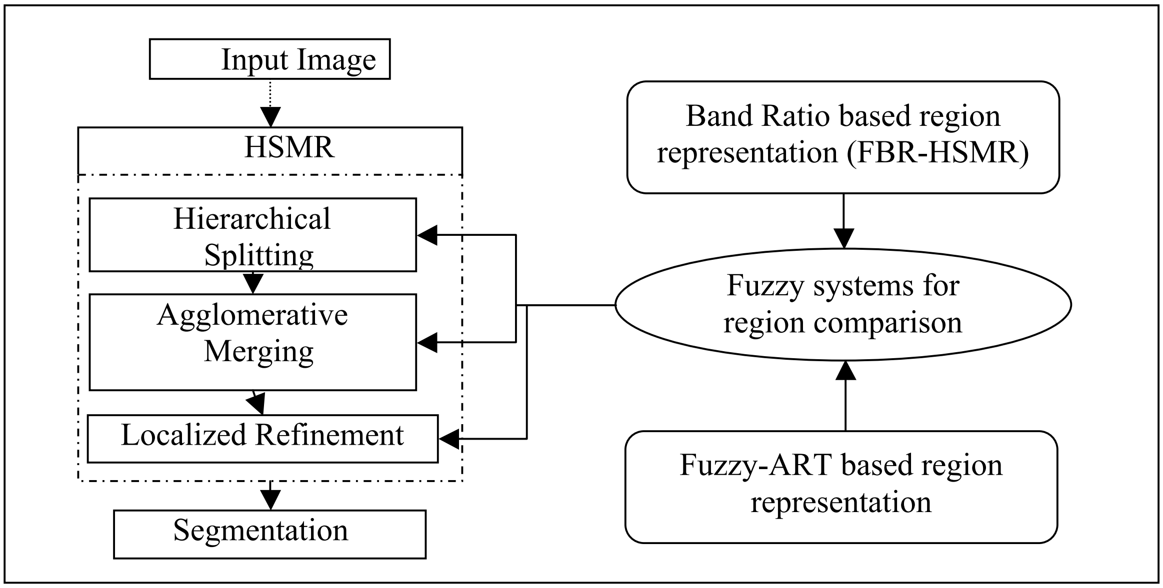

Figure 1.6: Overview of Fuzzy Band Ratio (FBR) and Fuzzy-ART augmentations of the HSMR Framework.

1.7.4 Supervised HSMR Solution

A supervised HSMR solution will be developed for VHR image segmentation. The building blocks for this solution will be:

a. Knowledge gained from unsupervised region based research (detailed in the previous sections);

b. Previous research proposed by Maxwell and Zhang [2006] on supervised segmentation; and

c. The Fractal Net Evolution Approach (FNEA) that is the basis of Definiens' *eCognition*™ Software's solution for image primitives.

The research detailed in sections 1.7.1 and 1.7.2 is based on unsupervised segmentation solutions. This is the general practice of segmentation solutions. The methodology proposed by Maxwell and Zhang [2006] is heavily dependent upon Definiens' Software and MathLab. The Maxwell and Zhang [2006] research developed a supervised method using fuzzy logic to merge image primitives, segmented by Definiens' *eCognition*™, into objects. The Maxwell and Zhang [2006] research proposed a method for dynamic parameter estimation. It, however, is for *localized* objects and estimations for one object may or may not be successful for all objects in a given scene. For details of the procedure, readers can refer to Maxwell and Zhang [2006].

In the new solution of the present research, the author will work first with a supervised solution that combines the knowledge of a, b, and c above. It is hypothesized that a supervised solution can be developed to improve segmentation of all objects in a scene rather than just individual objects.

1.7.5 Evaluation of Results

Regardless of any quantitative data, the results of segmentation are not successful unless they are pleasing to the eye. Visual analysis will be the primary method of evaluation. If required, a method of segmentation evaluation will be developed to compare different approaches. The results will be evaluated based on the following criteria:

a. Fragmentation;

b. Consistency;

c. Time; and

d. Operator Dependency

1.8 Overview of Each Chapter

As stated above **Chapter 1** gives information on VHR satellite imagery, segmentation, and problems associated with segmentation. In addition the structure of this thesis is outlined to provide the reader with addition information to the bridging chapters.

The paper in Chapter 2 addresses the methodology outlined in section 1.7.2 and 1.7.3. A review of the existing solution is presented in this paper with respect to the merging and refinement processes of the algorithm. Through these investigations and developments, a solution is presented for improving fragmentation and consistency in the HSMR algorithm by:

1. An improved refinement algorithm.
2. An improved method of halting the merging processes of the HSMR.

The primary focus of the paper in Chapter 2, however, is the introduction of a prior knowledge to segmentation through Band Ratios and Fuzzy Logic. This paper demonstrates how Band Ratios can be applied to the segmentation of VHR images to improve segmentation results. **Chapter 3** bridges the research presented in Chapter 2 to the research in Chapter 4.

The paper in Chapter 4 is an expansion of the work presented in Chapter 2. In this research Fuzzy Adaptive Resonance Theory (ART) is presented to replace the work of Band Ratios. These experiments attempt to validate the use of an unsupervised clustering of the input image to further automate and improve the research presented in Chapter 2. This work is part of the methodology discussed in section 1.7.3. **Chapter 5** bridges the research of Chapters 2 and 4 to the new supervised approach presented in Chapter 6.

The paper in Chapter 6 is the presentation of the supervised HSMR solution developed and discussed in section 1.7.4. This research presents a supervised solution that demonstrates how user parameter complexity is reduced to enable more control to the segmentation of VHR images.

A final summary chapter (**Chapter 7**) contains the conclusions of all the papers presented in this thesis. Recommendations for further research are discussed. The software design is included in the **Appendices**.

CHAPTER 2

REGION BASED SEGMENTATION OF QUICKBIRD MULTISPECTRAL IMAGERY THROUGH BAND RATIOS AND FUZZY COMPARISON

This chapter contains a journal paper which was originally published as:

Wuest, B., and Y. Zhang (2008). "Region Based Segmentation of QuickBird Multispectral Imagery through Band Ratios and Fuzzy Comparison." *ISPRS Journal of Photogrammetry and Remote Sensing,* (Accepted for publication, July, 2008)

The first author developed the algorithm and methodologies for the research presented in this paper. The second author gave advice in the research and journal paper writing. For the sake of clarity, the paper included in this chapter has been slightly edited.

Abstract

The continued advancements in satellite sensor technologies have increased the number of objects that can be discriminated within satellite imagery. Effective segmentation of high resolution satellite imagery is currently a hot topic of research. Existing segmentation algorithms and applications contain many parameters and options which require the operator to select a proper set of parameters for a given data set. The setting of these parameters can be quite tedious and the same set of parameters may or

may not work from one high resolution satellite image scene to the next. This paper presents a modification of a region based approach for unsupervised segmentation of high resolution satellite imagery as a solution to segmentation of land use coverage in QuickBird multispectral 2.44m imagery. This type of segmentation is important to a variety of applications such as land use classification and urban planning.

All region based segmentation approaches require a method for representing image regions/segments and judging the similarity between two given image regions/segments. In the proposed modification of this paper, region description is provided through the integration of band ratios. Region similarity measures are performed using Fuzzy Logic. The Hierarchical Split Merge Refinement (HSMR) algorithmic framework for unsupervised image segmentation is the foundation for this modification. In addition, this paper improves upon the merging and refinement processes of the HSMR algorithm. Test results demonstrate stable segmentation of land use areas across a variety of high resolution satellite images.

2.1 Introduction

Traditionally, remote sensing image classification has employed pixel-based procedures. These methods generally do not segment a given input image. Pixel based methods look to classify individual pixels through supervised or unsupervised classifiers such as Maximum Likelihood, K-Means, Multi-Layered Perceptrons and Fuzzy Adaptive

Resonance Theory (ART) [Liu et al, 2006]. Statistical measurements on individual pixel digital numbers (DNs) form inputs to these classifiers to classify individual pixels into pre-defined classes. It can be quite time consuming to obtain high levels of classification accuracy, using certain pixel based methods such as neural networks or fuzzy based classifiers, even on lower resolution imagery. This is shown by Aitkenhead and Dyer [2007] in their neural network based approach for improving land cover classification in Landsat TM imagery. Although pixel based methods have proven to be a generally successful method for classification of lower resolution satellite imagery, the advancements in image spatial resolutions have placed limitations on pixel based approaches and inadvertently led to new research activities for classification of high resolution satellite imagery. The object oriented paradigm is the basis for a majority of this research.

Object oriented classification asserts that regions/segments of an image are classified rather than individual pixels. The main advantage of object oriented methods is that researchers can analyze groups of pixels rather than individual pixels. As indicated by Benz et al. [2004], the close relationship between real-world objects and image objects provides a meaningful advantage to object-based methods. The object oriented paradigm can be combined with pixel based methods to form hybrid classification methods. Shackelford and Davis [2003] used Maximum Likelihood classification to partition pixels into broad categories and then employ a Fuzzy Classifier to provide refined object classification. A precursor to object oriented classification, however, is image segmentation. Objects cannot be classified if they are not isolated from within a given image. Segmentation represents the first step of any object based image analysis [Conchedda et al, 2008] and directly affects the quality of results.

There are many different approaches to the segmentation of high resolution imagery. Definiens *eCognition*™ software has emerged as a useful tool to experiment with parameters for segmentation within the object oriented paradigm. The segmentation approach employed by Definiens is detailed in Baatz and Schape [2000] and Benz et al. [2004]. A number of research endeavors have employed either the Definiens software or the underlying segmentation approach employed by Definiens. Examples can be found in Conchedda et al. [2008], Hay et al. [2003], Mallinis et al. [2008] and Xie et al. [2008] (to name a few). Image segmentation, from an algorithmic perspective, is generally divided into four categories: a) point-based, b) edge-based, c) region-based and d) combined [Schiewe, 2002]. For technical details of segmentation techniques, readers can refer to Pal and Pal [2003]. In this paper, the authors will focus on the modification and improvement of an unsupervised, region based, segmentation algorithmic framework, known as the Hierarchical Split Merge Refinement (HSMR) segmentation framework.

The HSMR framework was first introduced by Ojala and Pietikainen [1999]. It has been employed by Chen and Chen [2002] and more recently by Hu et al. [2005] in the field of remote sensing. Ojala and Pietikainen [1999] presented this framework to demonstrate the separation of textured regions in an image. Chen and Chen [2002] expanded on this work by introducing color measurements with slightly different algorithmic merging parameters. Hu et al. [2005] offered a thorough expansion of this framework by combining the textural ideas of Ojala and Pietikainen [1999] and color concepts of Chen and Chen [2002] in an adaptive approach. The methodology by Hu et al. [2005] does not limit measurements to a single feature but rather adaptively decides how to compare regions depending on their properties.

As stated by Hu et al. [2005], there are two key ingredients to the HSMR algorithmic framework for image segmentation,

- Region Representation; and
- Region Comparison.

Region representation is the method in which an image segment/region is represented mathematically. A region can be represented by any kind of measurement on the pixel digital numbers (DNs) within the image region such as color, texture, and area. A region can also be represented by shape characteristics such as compactness, smoothness and circularity. A histogram distribution has been the popular approach to region representation for integration with the HSMR algorithmic framework. Ojala and Pietikainen [1999] presented a texture-based region descriptor using a two-dimensional distribution of Local Binary Pattern and Contrast (LBP/C). Hu et al. [2005] also presented region representation as one and two-dimensional distributions of regions features. They employed saturation and hue as the features for a two-dimensional histogram representing the color of a given image region. A comprehensive review of other methods of region representation can be found in Trias-Sanz et al. [2008].

Region comparison is the method in which two image regions are compared based on their representation. There have been different methods for which region comparison has been presented for integration with the HSMR algorithmic framework. Ojala and Pietikainen [1999] employed a log-likelihood-ratio (G-Statistic) for judging region similarity. The G-Statistic indicates the probability that the information from two image regions come from the same population. Hu et al. [2005] used the correlation between feature histograms from two regions as a basis for their adaptive region similarity measure. Histogram correlation is dependent upon the resolution and dimensionality of the data.

This paper presents a Fuzzy Band Ratio (FBR) HSMR solution. This is a new HSMR modification which integrates band ratios and a fuzzy based similarity measure. In the new HSMR modification, region representation is calculated using the density of common land cover classes, such as vegetation, water, and urban features in a given region. Land cover information is calculated through band ratios. Using these methods for region representation, a Fuzzy Logic system is presented for region comparison. The purpose of this approach is to segment land cover categories in QuickBird 2.44 MS satellite imagery. With the integration of band ratios, this approach brings certain prior knowledge of image content to segmentation to provide consistent land cover segmentation in high resolution satellite imagery. In addition, this paper proposes modifications to HSMR merging and refinement processes to improve the overall segmentation result. Results of the Fuzzy Band Ratio (FBR) solution and generic

HSMR modifications demonstrate a viable solution for land cover segmentation of QuickBird multispectral 2.44m imagery.

2.2 Background

The Hierarchical Split Merge Refinement (HSMR) segmentation framework was first proposed by Ojala and Pietikainen [1999]. As Figure 2.1 indicates, the framework consists of three essential stages in which i) the input image is split into a set of objects where uniformity measures fail, ii) resulting objects are merged into a set of approximate objects under a Merge Importance (MI) criterion and iii) the approximated objects are refined using localized border measures. All sections of this segmentation framework operate under the restrictions of a predetermined approach for region description and comparison.

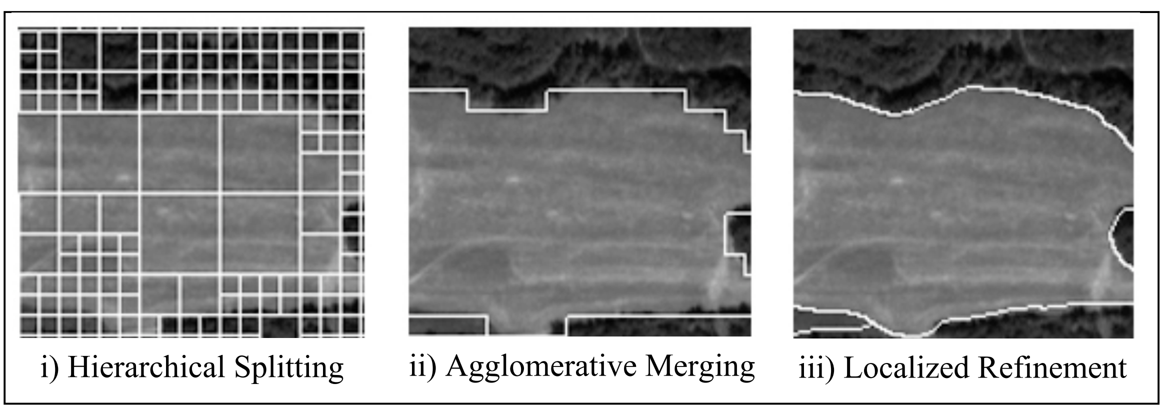

Figure 2.1: The three essential stages of Hierarchical Split Merge Refinement (HSMR) - an unsupervised segmentation framework.

The following sub-sections will discuss the HSMR merging and refinement processes for further understanding the proposed algorithmic modifications to be discussed in the methodology section of this paper. For complete details of the HSMR decision processes, including hierarchical splitting (not discussed here), readers can refer to Ojala and Pietikainen [1999].

2.2.1 Agglomerative Merging

Agglomerative merging is an iterative process, introduced by Ojala and Pietikainen [1999]. Ojala and Pietikainen [1999] define a Merger Importance (MI) value on a possible merge between two image regions/segments. The process can be viewed as a global best fitting approach in which all possible merges, at a given merge iteration, are evaluated by their MI. Equation (2.1) is the original definition of MI defined by Ojala and Pietikainen [1999] which uses the distance *G* between the two image regions. Equation (2.2) is the MI definition proposed by Chen and Chen [2002] which uses the similarity *H* between the two image regions. In both equations, p is the area of pixels of the smaller of the two given image regions.

$$MI = p \times G \tag{2.1}$$

$$MI = 1/\sqrt{p} \times H \tag{2.2}$$

Table 2.1 tabulates the optimal selection method, merging stop condition and corresponding thresholds for each definition of MI. In Table 2.1, MI_{CUR} is the MI optimally selected for a given merge iteration. As shown in Table 2.1, the optimal selection depends on the definition of MI. MI_{MAX} and MI_{MIN} are the maximum and minimum MI found up to the current merge iteration. T , T_1 and T_2 are predefined thresholds set on the agglomerative merging process. These thresholds are set by the user prior to segmentation.

Table 2.1: Optimal selection methods and stop conditions for different MI definitions.

MI Definition	Optimal Selection	Merge Stop Condition (MSC)
Equation (2.1)	MIN(MI)	$MI_{CUR} / MI_{MAX} > T$
Equation (2.2)	MAX(MI)	$(MI_{CUR} / MI_{MIN} < T_1)$ OR $(MI_{CUR} / MI_{MAX} < T_2)$

2.2.3 Localized Border Refinement

Localized border refinement was originally proposed by Ojala and Pietikainen [1999] in their study of unsupervised texture segmentation. The iterative process is detailed by the following steps,

- All boundary pixels BP_i are found and marked;
- Each BP_i is then inspected by placing a disc of radius r around the pixel;
- The distance G between the disc and any connected region is calculated; and

- The body containing the smallest distance G is recorded. If this body is not the body to which BP_i is currently assigned to and there is at least one 4-connected pixel in the neighborhood of the boundary to the new body assignment then the pixel is moved.

This process is repeated iteratively on pixels in the neighborhood of pixels that were relabeled on the previous sweep. Ojala and Pietikainen [1999] proposed that sweeps are continued until no pixels are re-labeled or until a set maximum number of iteration is reached. Chen and Chen [2002] expanded this by proposing that the distance G be replaced by a score measure $(Score = \sqrt{v_a} \times H)$. In this measure, H is the similarity of the regions while v_a represents the number of 4 neighbors of BP_i which are labeled to the *a*th region. The Chen and Chen [2002] score measure reduces fragmentation in segmentation results.

2.3 Methodology

This section outlines the proposed Fuzzy Band Ratio (FBR) HSMR solution along with the proposed HSMR algorithmic modifications. As stated earlier, the HSMR segmentation framework requires a method of region description and region comparison to make unsupervised decisions in splitting, merging, and refining image regions. The proposed approach to region description employs band ratios as a foundation to bring certain prior knowledge into the segmentation decision processes. Using this region representation, a Fuzzy system is presented to perform region comparison for HSMR processes. Figure 2.2 outlines an overview of the integration presented.

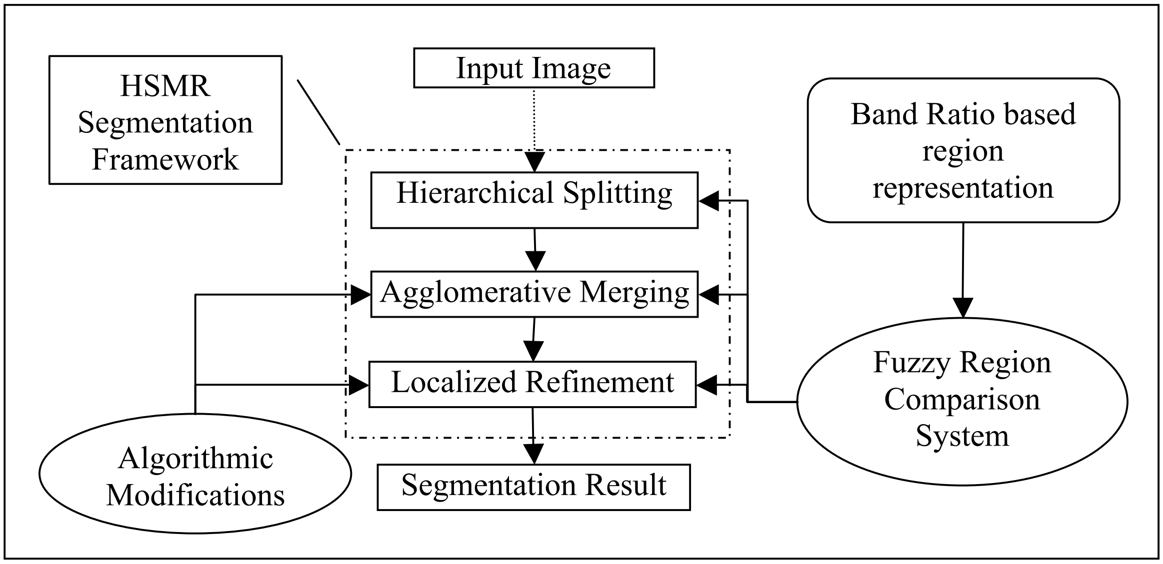

Figure 2.2: Overview of Fuzzy Band Ratio (FBR) HSMR solution and generic HSMR algorithmic modifications.

2.3.1 Integration of Band Ratio to Region Description

Five classes of interest: Forest (F), Grass (G), Soil (S), Water (W), and Urban (U) corresponding to general land cover classes found in remote sensing imagery are used in this integration. The Normalized Difference Vegetation Index (NDVI) proposed by Tucker (1979), a Water Ratio Index (WRI) from discussion in Navulur (2007) and the blue/red ratio are employed to identify suspected pixels belonging to each class.

$$NDVI = (NIR - R)/(NIR + R) \tag{2.3}$$

$$WRI = NIR/B + R/B + G/B \tag{2.4}$$

$$BR_{RATIO} = B/R \tag{2.5}$$

In addition, entropy is employed as a texture measurement to separate the classes of Grass (G) and Forest (F) (see Figure 2.3). Figure 2.3.b is the NDVI ratio image where Forest (F) and Grass (G) are spectrally separable as a group. In Figure 2.3.c, the entropy ratio image demonstrates the separation of the two land cover classes isolated by the NDVI. Equation (2.6) is Shannon and Weaver's entropy equation [Shannon and Weaver, 1949]. This equation calculates the entropy of a given green pixel (G) using the probability distribution function (PDF) of the 3x3 localized window.

$$H(G) = -\sum_{i=M}^{N} p(g_i)\log(p(g_i)) \tag{2.6}$$

In Equation (2.6), [M,N] is dynamically determined from the PDF of the green image band. This range encompasses the majority of the information in the green PDF and is used to avoid including noise in the local entropy calculations. In Equation (2.6), $p(g_i)$ is the probability associated with g_i in the given local window.

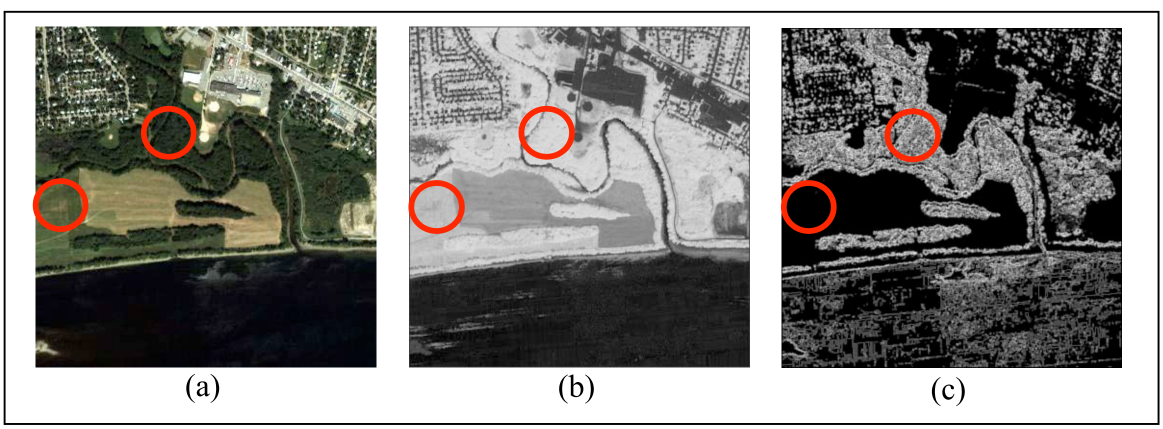

Figure 2.3: NDVI ratio and green band entropy image demonstrating the separation of Forest (F) and Grass (G). (a) Original (b) NDVI ratio image and c) Green entropy image.

Each class is represented by a band ratio function (BRF) which defines a class membership condition (see Table 2.2). The band ratio functions (BRFs) produce a value of 1 if a given pixel meets the conditions of the function for the class.

Table 2.2: Band Ratio Function Class Membership Conditions

CLASS (c)	**Band Ratio Function Class Membership Condition**
Forest (F)	NDVI > 0.55 AND H(G) >= 0.1
Grass (G)	NDVI > 0.55 AND H(G) < 0.1
Water (W)	WRI <= 2.5
Soil (S)	(NDVI <= 0.55 AND NDVI >= 0.2) AND (B/R) <= 1.5
Urban (U)	(NDVI < 0.2) AND (WRI > 2.5)

Using the band ratio functions, image regions can be described by their class densities. For any given region, the density *d* for a class *c* is obtained by the ratio of the sum of the BRF for that class within the region's pixels over the region's total area (in pixels).

$$d(c,r) = \sum_{i}^{M} \sum_{i}^{N} BRF_C(i,j) \Big/ area(r) \tag{2.7}$$

In Equation (2.7), c represents the pre-defined class and r represents the image region. BRF_C is the band ratio function corresponding to class c. Using the densities of all predefined classes, a class density vector *(CDV)* is produced to describe a given image region. Equation (2.8) outlines the *CDV* for an image region *r*.

$$CDV(r) = \{d(F,r), d(G,r), d(S,r), d(W,r), d(U,r)\} \tag{2.8}$$

Figure 2.4 displays some example image regions and their corresponding density vectors. While Figure 2.4.b shows a region with approximately 28% forest, 20% grass, 10% soil, 0% water and 10% urban, Figure 2.4.a shows a region containing approximately all water.

	Image Region *r*	$CDV(r)$
[a]		{ 0.00, 0.00, 0.00, 0.94, 0.00 }
[b]		{ 0.28, 0.20, 0.10, 0.00, 0.10 }

Figure 2.4: Sample regions and their corresponding class density vectors.

2.3.2 Fuzzy integration in *HSMR* decision processes

The processes of the HSMR algorithmic framework require a method of comparing regions. For more in-depth details of HSMR processes, readers can refer to Ojala and Pietikainen [1999]. In this research, a Fuzzy System is presented to evaluate the similarity of two image regions. The Fuzzy Similarity System (FSS) produces a value in the range [0, 1], where 0 indicates that there is no similarity between the two image regions and 1 indicates extreme similarity. There are three fuzzy input variables (introduced in Table 2.3) employed by the proposed Fuzzy Similarity System (FSS). The first two variables in Table 2.3 are measurements on the class density vectors (CDV) of two given image regions. These variables measure the common class density (Common Density) and the difference in class density (Density Dissimilarity). The equations for Common Density (CD) and Density Dissimilarity (DD) are presented in Equations (2.9) and (2.10). In both equations, R_a and R_b are the two image regions for comparison.

$$CD(R_a, R_b) = \sum_{i=1}^{N} CDV(R_a)_i \wedge CDV(R_b)_i \tag{2.9}$$

In Equation (2.9), the *fuzzy min intersection* operator is applied to the corresponding class density vectors elements from each image region. The sum of the resulting vector yields the common class density between the two regions in question.

$$DD(R_a, R_b) = \left\| CDV(R_a) - CDV(R_b) \right\| \qquad (2.10)$$

As indicated in Equation (2.10), DD is the Euclidean distance between the class density vectors for the two given image regions. The third variable, Area Ratio (AR), is the ratio of the minimum region area over the maximum region area.

$$AR(R_a, R_b) = \min(A(R_a), A(R_b)) / \max(A(R_a), A(R_b)) \qquad (2.11)$$

In Equation (2.11), R_a and R_b are the image regions being compared. A(x) is the area in pixels of region x.

Table 2.3: Fuzzy System Input Variables (Graphical Details in Figure 2.5)

Variable	**Fuzzy Number Set**	**Linguistics**
Common Density (CD)	{ (0.0,0.0,0.05,0.1), (0.05,0.1,0.25,0.30), (0.25,0.30,0.60.0.65), (0.6,0.65,0.8,0.85), (0.8,0.85,1.0,1.0) }	{ no cd, low cd, medium cd, high cd, full cd }
Density Dissimilarity (DD)	{ (0.0,0.0,0.20,0.25),(0.20,0.25,0.45,0.50), (0.45,0.50,0.70,0.75), (0.70,0.75,1.0,1.1), (1.0,1.1,1.5,1.5)}	{ no dd, low dd, medium dd, high dd, full dd }
Area Ratio (AR)	{ (0.0,0.0,0.1,0.15), (0.1,0.15,1.0,1.0) }	{ low ar, high ar}

A graphical representation of FMS inputs and outputs is provided in Figure 2.5. The universal discourse of FMS system output Similarity (S) is defined as S = { no similarity, low similarity, medium similarity, high, similarity, full similarity } = { ns, ls, ms, hs, fs } and is illustrated graphically in Figure 2.5.d. S is represented by the set of fuzzy numbers α = { (0.0,0.0,0.10,0.20), (0.1,0.30,0.30,0.50), (0.30,0.50,0.50,0.70), (0.50,0.70,0.70,0.90), (0.80,0.90,1.0,1.0) }. The complete rule base for the FMS is displayed in Table 2.4.

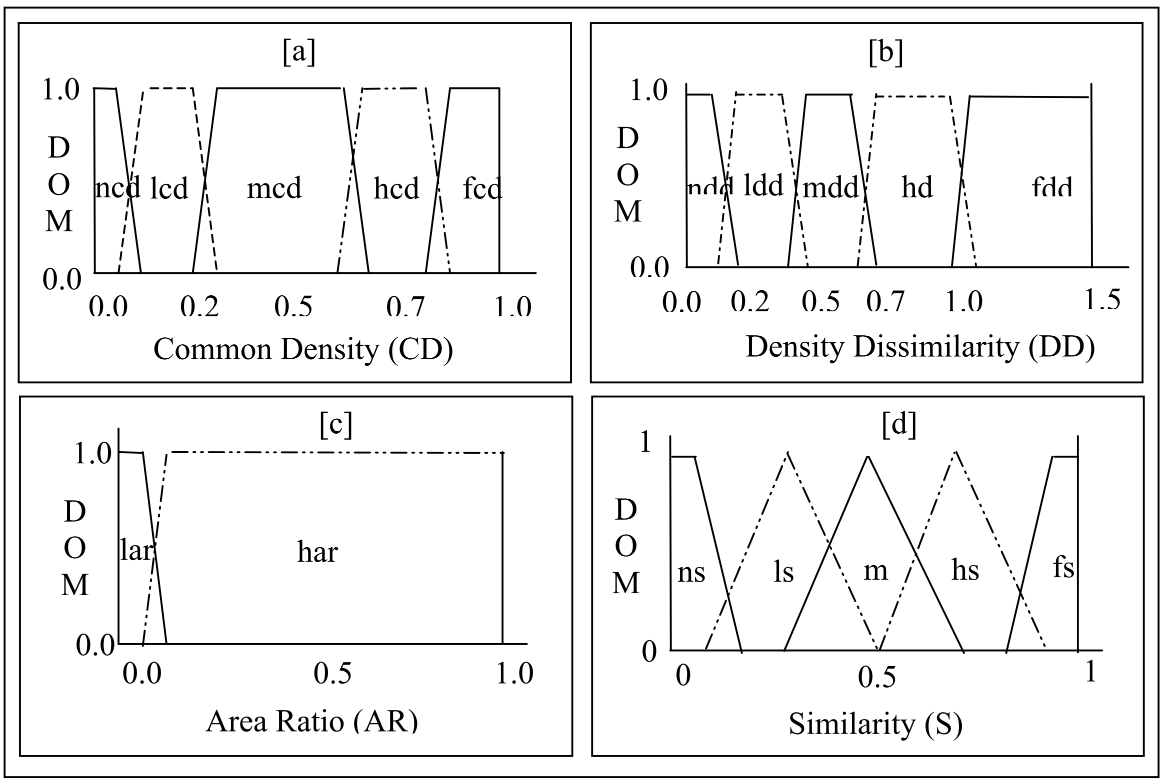

Figure 2.5: Fuzzy membership functions for FMS input and output variable(s). a) Common Density, b) Density Dissimilarity, c) Area Ratio and d) Similarity.

Table 2.4: Fuzzy Similarity System (FSS) Rules

Rule	Condition
1	IF (ncd OR fdd) OR (lcd AND hdd) THEN ns
2	IF (lcd and mdd) OR (mcd AND hdd) OR (mcd AND mdd and har) OR (hcd AND hdd AND har) THEN ls
3	IF (lcd AND lar AND (ndd OR ldd)) OR (mcd AND lar AND mdd) OR (hcd AND lar AND hdd) OR (hcd AND har AND mdd) OR (fcd AND hdd) THEN ms
4	IF (lcd AND ldd AND lar) OR (mcd AND har AND (ndd OR ldd)) OR (hcd AND mdd AND lar) OR (hcd AND ldd AND har) OR (fcd AND mdd) THEN hs
5	IF (NOT(ncd) AND lar AND ndd) OR (NOT(ncd OR lcd) AND lar AND ldd) OR ((hcd OR fcd) AND ndd) OR (fcd AND ldd) THEN fs

2.3.3 Agglomerative Merging Modifications

As illustrated in Table 2.1, definitions of MI are accompanied by a corresponding merging stop condition. In this modification, a merging stop condition is proposed for both definitions of Merger Importance (MI). The basis of this approach is the measure of distance (D) between all remaining objects and their neighbors at a given merge iteration. It is observed that when merging is approaching an optimal solution, a) the average distance between neighboring objects is substantially increasing and b) the variance of distance between neighboring objects is substantially decreasing. This is shown graphically in Figure 2.6. As the optimal merging solution is approached (in this case iteration 2383), $\mu(D)$ is increasing and $\sigma(D)$ is decreasing substantially.

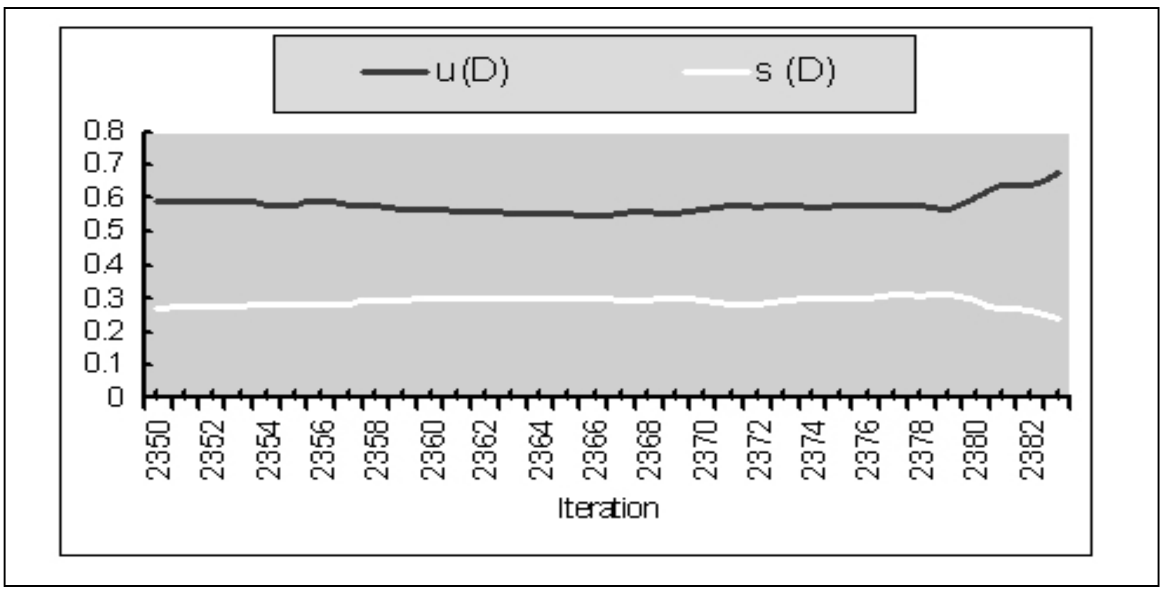

Figure 2.6: The graphical representation of $\mu(D)$ and $\sigma(D)$ as merging is approaching optimal merging result (2383)

It is impossible to set a hard threshold on $\mu(D)$ or on $\sigma(D)$ because of the considerable variety in satellite image scenes. What can be measured, however, is the ratio of $\sigma(D)$ at the current merge iteration over $\sigma(D)$ at the previous iteration.

$$\sigma(D)_{RATIO}(i) = \sigma(D)_i / \sigma(D)_{i-1} \quad (2.12)$$

In Equation (2.12), i is the current iteration and $\sigma(D)_i$ and $\sigma(D)_{i-1}$ are the standard deviation of the distances between neighboring objects at the current and previous merge iterations. Figure 2.7 graphs $\sigma(D)_{RATIO}(i)$ over the iterations shown in Figure 2.6. As the optimal merging solution is approached (iteration 2383) the sigma ratio is decreasing drastically.

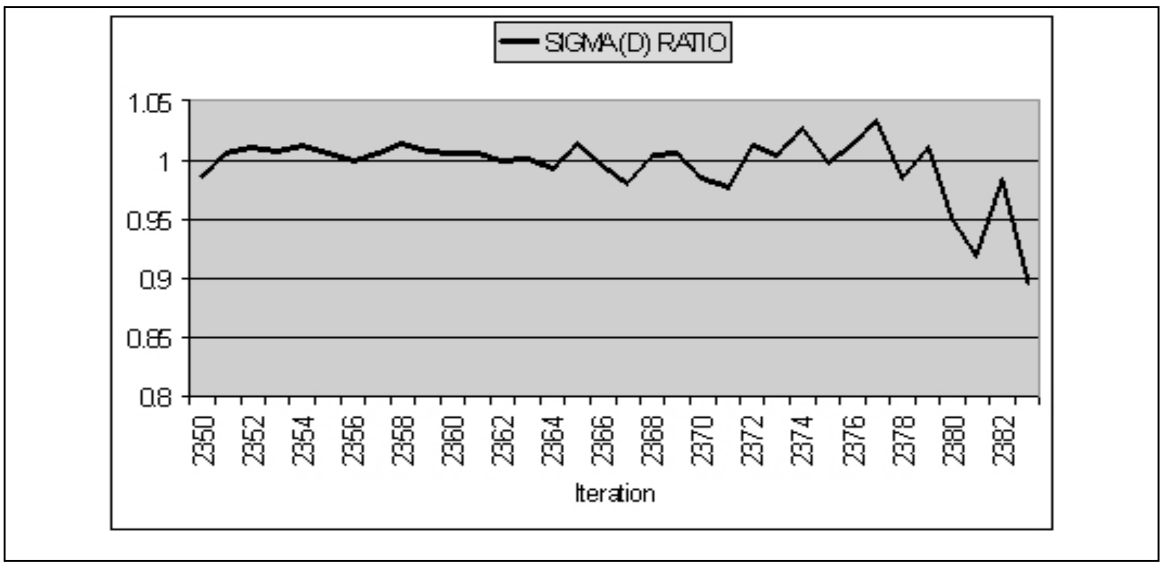

Figure 2.7: The graphical representation of $\sigma(D)_{RATIO}(i)$ over the iterations shown in Figure 2.6. There is a steep decrease as the optimal merging is approached.

In the proposed modification, a merging threshold (MT) is defined on $\sigma(D)_{RATIO}(i)$ as a merging stop condition. The setting of MT is dependent upon the similarity measure employed by the HSMR algorithm. For the FBR integration, presented in this paper, it was empirically determined that 0.9 was a good measure for MT.

2.3.4 Pixel-wise Refinement Modifications

In this study, two problems were observed in the pixel wise refinement process,

- Non-contiguous Regions; and
- Similar Neighbors.

When a region becomes non-contiguous it should be viewed as two regions instead of one. The existing refinement algorithm does not account for this refinement behavior. This is represented in Figure 2.8. In Figure 2.8.a the regions for refinement (A and B) are close to one another. In Figure 2.8.b it is demonstrated how region B refines itself through region A. This causes region A to be non-continuous. The desired refinement result of A is presented in Figure 2.8.c.

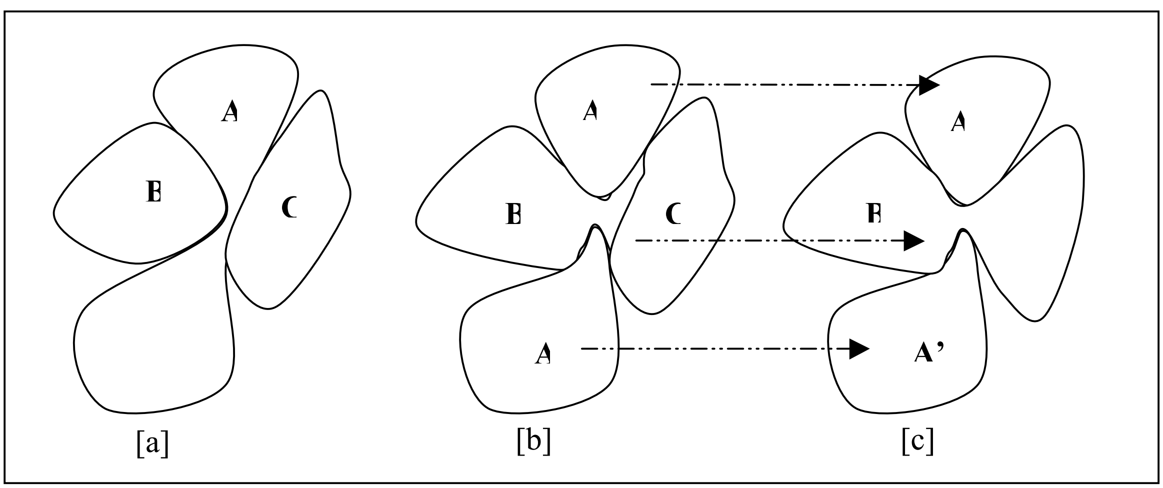

Figure 2.8: Non-contiguous and similar regions and the desired result. [a] Example region scenario. [b] Refinement result using traditional refinement algorithm. [c] The desired result.

When two neighboring regions are very similar, they should be merged together. If they are not merged together they will continue to fight for border pixels and cause the number of iterations required for refinement to increase dramatically. Figure 2.8.b demonstrates this issue, showing region B and C next to each other fighting for boundary pixels. The desired result is represented in Figure 2.8.c where region C is merged into region B.

To combat these problems with segmentation the following iterative process is proposed:

- Process the image using the improved score measure by Chen and Chen [2002] in the algorithmic approach presented by Ojala and Pietikainen [1999];
- Collect all the continuous regions in the image determined by this process;
- Count the regions collected. Stop if over 5 iterations or if the number of regions is equal to that of the previous iteration;
- Identify all the boundary pixels; and
- Return to step 1.

This process is repeated until the number of continuous regions collected is equal to the number collected at the previous iteration or a maximum number of iteration has been reached. Through empirical observation, it was determined that most scenes will reach a common region count within 5 iterations.

The above iterative process addresses the problem of non-contiguous regions. In addition, during border pixel inspection, the similarity between bordering regions is calculated. If the similarity between the regions is over a Threshold T, the regions in question are immediately merged. A similarity threshold of 0.85 is employed to ensure that there is strong similarity between two adjacent regions. If two regions are merged in this procedure, the border of this new region is marked for further inspection.

2.4 Experiments

The proposed Fuzzy Band Ratio (FBR) HSMR solution and generic HSMR modifications were tested using QuickBird multispectral 2.44m imagery. The test imagery presented here contains scenes with a variety of land cover classes. This includes areas containing water features, urban development, and a variety of vegetation and soil areas. The image size employed for all test scenes is 512 x 512 pixels.

A number of parameters were set on the FBR HSMR algorithmic framework. Unless otherwise indicated, the hierarchical splitting parameters for maximum window size (S_{MAX}) and minimum window size (S_{MIN}) were set to 64 and 8 respectively. The splitting trigger X for hierarchical splitting used by these tests is 1.1. The splitting trigger X is a parameter to the hierarchical splitting processes of the HSMR. For more in-depth details regarding hierarchical splitting or any of the mentioned HSMR parameters, readers can refer to Ojala and Pietikainen [1999]. In agglomerative merging, MT is set to 0.9 for all FBR results. Within pixel-wise refinement, the maximum number of iterations is 300 and refinement is stopped when no more border pixels are available for inspection.

2.4.1 Multispectral Image Segmentation

The results of the Fuzzy Band Ratio (FBR) HSMR on QuickBird multispectral 2.44m imagery are displayed in Figure 2.9. The results demonstrate the segmentation of land cover classes. Figure 2.9.a demonstrates the ability to distinguish tree areas, mixed tree and grass areas from the more urban cover in a suburban scene. In Figure 2.9.b the FBR HSMR performs quite well on a very difficult suburban scene. For the result in Figure 2.9.b, (S_{MIN}, S_{MAX}) is set to (8, 32) because of the scene complexity. Figure 2.9.c presents another scene similar to Figure 2.9.a. Figure 2.9.d is a port scene with a large amount of water. The urban features are separated from the vegetation and water correctly.

Figure 2.9: Automatic segmentation of QuickBird 2.44m multi-spectral imagery using the proposed FBR HSMR with generic algorithm modifications.

2.4.2 Comparison with Color Based Segmentation

Figure 2.10 shows a comparison between FBR and RGB based segmentation. The distance measure for this RGB segmentation is the average of the correlation between the three color bands (a simple approach). Because the RGB measure is based on correlation, a dynamic range for (S_{MIN}, S_{MAX}) of (16, 64) is employed. As is indicated in Figure 2.10.b, the RGB based segmentation has difficulty in several places. The algorithm settles on multiple water regions because of the color variation in the water. The small island region in the top right is over merged into the water and a large scale urban feature in the bottom right is segmented as part of a water region. This example demonstrates how the prior knowledge introduced by the FBR HSMR enables segmentation to collect the proper regions for identifying land cover.

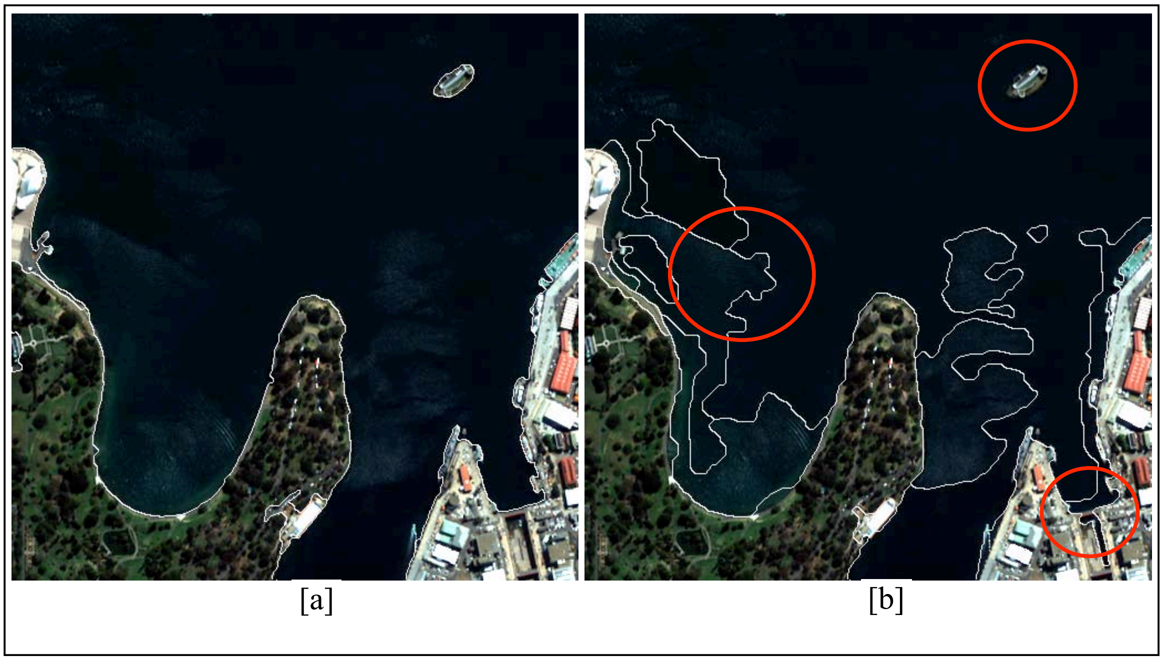

Figure 2.10: FBR comparison with RGB based segmentation of scene Figure 2.9.d. a) FBR Segmentation with MT = 0.90. b) RGB based segmentation using proposed HSMR modifications with MT = 0.95. Problems circled from top to bottom identify: i) an over merged island, ii) over segmented water areas and iii) inclusion of urban features with water regions.

2.4.3 Modified Agglomerative Merging

The proposed modifications implement a method for halting the agglomerative merging process. As indicated earlier, the merging threshold (MT) was set to 0.90 for all FBR HSMR experiments. Experiments were performed to determine if the proposed modifications would be successful and consistent on different MI definitions. These results were compared against the previously defined merge stop conditions for different MI definitions (see Table 2.1). Figure 2.11 displays these results, which demonstrate that the modified merging is able to perform consistently on different MI definitions in FBR segmentation.

For the MI defined in Equation (2.2), the thresholds for T_1 and T_2 were set to 0.68 and 0.09 in accordance with the published parameters (see Chen and Chen [2002]). The threshold T for the MI defined in Equation (2.1) was set to 1.5. Figure 2.11 displays two images. For each image there are four segmentation results displayed (a, b, c and d). These results, explained by letter are: a) Proposed merging with MI definition from Equation (2.2); b) Proposed merging with MI definition from Equation (2.1); c) MI defined in Equation (2.2) and its corresponding merging method; and d) MI defined in Equation (2.1) and its corresponding merging method. Through FBR HSMR testing, the proposed merging modifications were found to be as successful as the Chen and Chen [2002] merging approach and more consistent than Ojala and Pietikainen [1999] merging approach. This is apparent in Figure 2.11. The images in Figure 2.11.1.d and 2.11.2.d are both under segmented.

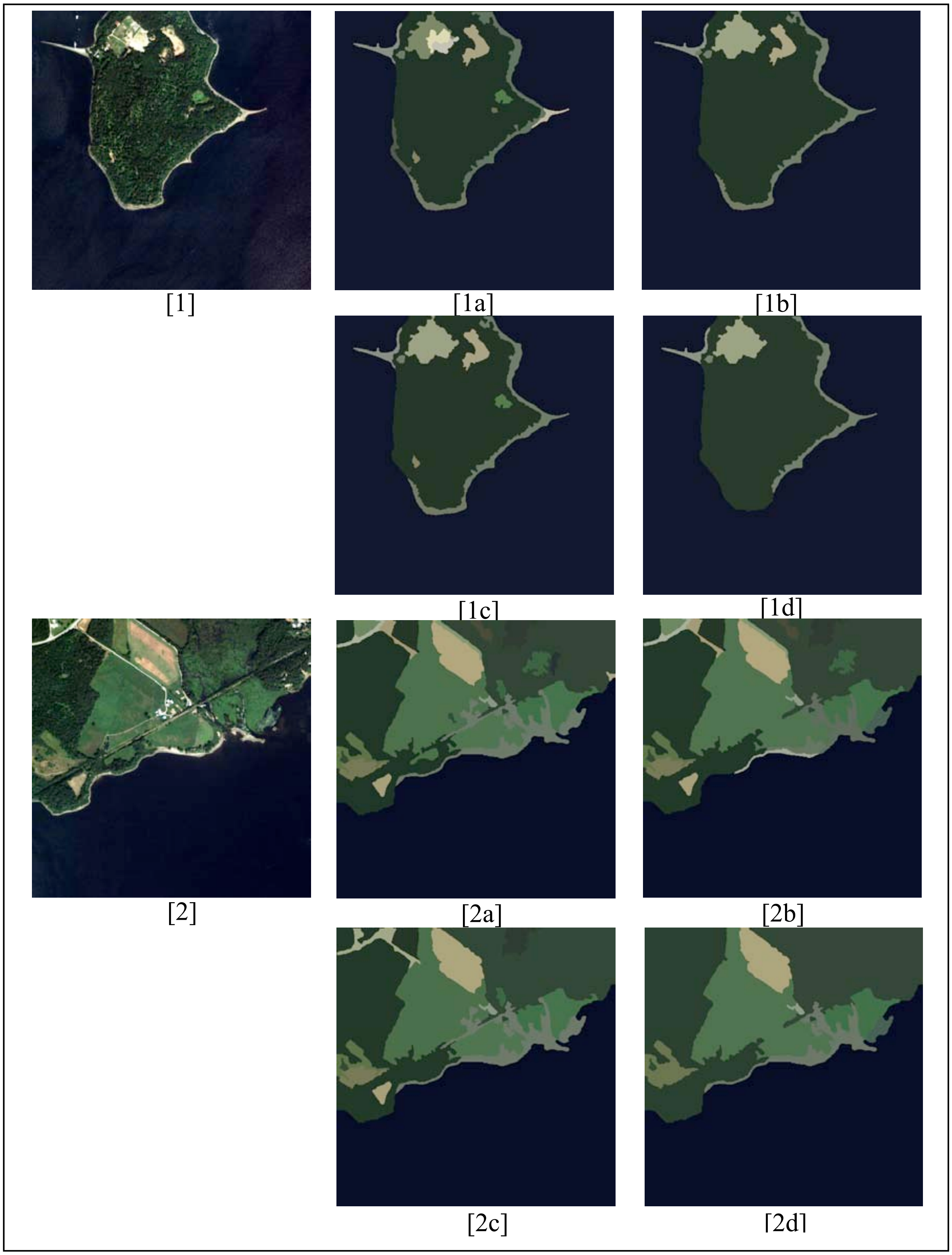

Figure 2.11: Results of FBR HSMR Segmentation with modified agglomerative merging.

2.4.4 Modified Pixel-wise Refinement

Figure 2.12 demonstrates the effects of our improved pixel-wise refinement, which addresses non-contiguous regions and similar neighboring regions. In Figure 2.12.a and Figure 2.12.b the original specifications proposed by Ojala and Pietikainen [1999] and the proposed Fuzzy Band Ratio solution are employed. The distance measure proposed by Ojala and Pietikainen [1999] is employed in Figure 2.12.a and the score measures, proposed by Chen and Chen [2002] are employed in Figure 2.12.b. Fragmentation (indicated in Figure 2.12.a) in this scene is removed but there is still a small redundant region that really belongs to the region of mixed grass and soil. In Figure 2.12.c the results of the Fuzzy Band Ratio HSMR using the score measures of Chen and Chen [2002] and the refinement modifications are displayed. Fragmentation and the redundant region are not present in Figure 2.12.c.

[a] Fragmentation [b] Redundancy [c]

Figure 2.12: Results of the proposed Fuzzy Band Ratio (FBR) HSMR solution with different refinement parameters. a) distance measure from Ojala and Pietikainen [1999], b) score measures from Chen and Chen [2002], c) proposed refinement modifications with score measures from Chen and Chen [2002].

2.5 Discussion and Conclusions

This paper presents a Fuzzy Band Ratio (FBR) HSMR solution for segmentation which involves, i) the integration of band ratios to region description and ii) Fuzzy Logic based similarity measure. The experiments demonstrate that the proposed FBR HSMR solution presents another promising method for high resolution image segmentation using the HSMR framework. The proposed band ratio integration for region representation provides a means for this unsupervised segmentation framework to identify objects of the same categories consistently. It provides the framework with a certain prior knowledge of the content in a given image. Decisions for splitting, merging and refinement are made using this knowledge through the proposed fuzzy similarity system.

The proposed fuzzy similarity system for region comparison is not as prone to inaccuracy in smaller region sizes as other similarity measures (such as correlation). As a result, the initial block sizes (the minimum and maximum window sizes (S_{MIN}, S_{MAX}) used by the initial splitting component of the HSMR algorithm) employed by the proposed integration are in a greater dynamic range than past research. A $(S_{MIN}, S_{MAX}) =$ (8, 64) is employed by the proposed integration, whereas the majority of other HSMR research has reported $(S_{MIN}, S_{MAX}) = (16, 64)$ [Hu et al., 2005, Chen and Chen, 2002]. The proposed integration is able to operate using $(S_{MIN}, S_{MAX}) = (4, 64)$ for some imagery but overall consistency was observed to occur using $(S_{MIN}, S_{MAX}) = (8, 64)$. This increased dynamic range leads to more optimal region approximation.

The proposed modifications to HSMR merging and refinement processes improve the existing HSMR algorithmic foundation. As demonstrated in the experiments section, the refinement modifications produce a more consistent refinement by removing the possibility for non-continuous regions and region redundancy. Without these modifications, the refinement process can be time consuming and produce variable results depending on slight adjustments in the merging process. The integration of the proposed agglomerative merging modifications with both the MI definitions (Ojala and Pietikainen [1999] and Chen and Chen [2002]) is demonstrated successfully. These merging modifications are found to be more consistent over a variety of imagery in reducing undesired segmentation results.

The wide range of scenes in high resolution satellite imagery may inhibit the proposed algorithm from performing perfectly every time. However, as has been demonstrated, the method is quite capable of segmenting regions into rough land coverage classes. Although there is still room for future improvements, such as 1) dynamic category/class determination, 2) simplification of Fuzzy System Inputs, and 3) dynamic parameter selection, we conclude that the experiments presented here are viable.

Acknowledgements

The authors would like to recognize the support of DigitalGlobe® and the City of Fredericton, New Brunswick, Canada for providing the imagery for this experimentation and Mr. Lawrence J. Wuest for his comments and suggestions. The research is funded by the second author's NSERC Discovery Grant.

References

Aitkenhead, M.J. and R. Dyer (2007). "Improving Land-cover Classification Using Recognition Threshold Neural Networks." *Photogrammetric Engineering & Remote Sensing*, Vol. 74, No. 4, pp. 413-421.

Baatz, M. and A. Schape (2000). "Multiresolution segmentation – an optimization approach for high quality multi-scale image segmentation." *Angewandte Geographische Informations-Verarbeitung XII*. Ed. J. Strobl et al. AGIT Symposium, Salzburg, Germany, 2000. pp. 12-23. [Internet], cited 22 July 2008. Available in .pdf format through http:/www.definiens-imaging.com/documents/reference.htm.

Benz, U.C., Hofmann, P., Willhauck, G., Lingenfelder, I. and M. Heynen (2004). "Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information." *ISPRS Journal of Photogrammetry & Remote Sensing*, Vol. 58, No. 3-4, pp. 239-258.

Bojadziev, G. and M. Bojadziev (1995). *Fuzzy Sets, Fuzzy Logic, Applications*. World Scientific Publishing, River Edge, NJ.

Cha, S.H. and S.N. Srihari (2002). "On measuring the distance between histograms." *Pattern Recognition,* Vol. 35, No. 6, pp. 1355-1270.

Chen, K.M. and S.Y. Chen (2002). "Color texture segmentation using feature distributions." *Pattern Recognition Letters,* Vol. 23, No. 7, pp. 755-771.

Cheng, H., Jiang, X.H., Sun, Y and J. Wang (2001). "Color image segmentation: advances and prospects." *Pattern Recognition,* Vol. 34, No. 12, pp. 2259-2281.

Conchedda, G., Durieux, L. and P. Mayaux (2008). “An object-based method for mapping and change analysis in mangrove ecosystems.” *ISPRS Journal of Photogrammetery & Remote Sensing*, DOI:10.1016/j.isprsjprs.2008.04.002.

Hay, G.J., Blaschke, T., Marceau, D.J. and A. Bouchard (2003). “A comparison of three image-object methods for the multiscale analysis of landscape structure.” *ISPRS Journal of Photogrammetry & Remote Sensing*, Vol. 57, No. 5-6, pp. 327-345.

Hu, X., Tao, C.V. and B. Prenzel, B (2005). “Automatic segmentation of high-resolution satellite imagery by integrating texture, intensity, and color features.” *Photogrammetric Engineering & Remote Sensing*, Vol. 71, No.12, pp. 1399-1406.

Liu, Y., Li, M., Mao, L. and F. Xu (2006). “Review of remotely sensed imagery classification patterns based on object oriented image analysis.” *Chinese Geographical Science,* Vol.16, No. 3, pp. 282-288.

Mallinis, G., Koutsias, N., Tsakiri-Strati, M. and M. Karteris (2008). “Object-based classification using Quickbird imagery for delineating forest vegetation polygons in a Mediterranean test site.” *ISPRS Journal of Photogrammetery & Remote Sensing,* Vol. 63, No. 2, pp. 237-250.

Navulur, K (2007). *Multispectral Image Analysis Using the Object-Oriented Paradigm*. CRC Press, Boca Raton, FL.

Nichol, J. and C.M. Lee (2005). “Urban vegetation monitoring in Hong Kong using high resolution multispectral images.” *International Journal of Remote Sensing*, Vol. 26, No. 5, pp. 903-918.

Ojala, T. and M. Pietikainen (1999). “Unsupervised texture segmentation using feature distributions.” *Pattern Recognition,* Vol. 32, No. 3, pp. 477-486.

Ojala, T., Pietikainen, M. and D. Harwood (1996). “A comparative study of texture measures with classification based on feature distributions.” *Pattern Recognition,* Vol. 29, No. 1, pp. 51-59.

Pal, N.R. and S.K. Pal (1993). “A review on image segmentation techniques.” *Pattern Recognition*, Vol. 26, No. 9, pp.1277–1294.

Schiewe, J (2002). “Segmentation of high-resolution remotely sensed data – concepts applications and problems.” *Joint International Symposium on Geospatial Theory, Processing and Applications.* Ottawa, Canada. [Internet], cited 22 July 2008. Available in .pdf format through http:/www.definiens-imaging.com/documents/reference.htm.

Shackelford, A.K. and C.H. Davis (2003). "A hierarchical fuzzy classification approach for high-resolution multispectral data over urban areas." *IEEE Transactions on Geoscience and Remote Sensing,* Vol. 41, No. 9, pp. 1920-1932.

Shannon, C.E and W. Weaver (1949). The Mathematical Theory of Communication. The University of Illinois Press, Champaign, IL.

Trias-Sanz, R., Stamon, G. and J. Louchet (2008). "Using colour, texture, and hierarchical segmentation for high resolution remote sensing." *ISPRS Journal of Photogrammetry & Remote Sensing*, Vol. 63, No. 2, pp. 156-168.

Tucker, C.J. (1979). "Red and photographic infra-red linear combinations for monitoring vegetation*." Remote Sensing of Environment*, Vol. 8, No. 2, pp. 127-150.

Xie, Z., Roberts, C. and B. Johnson (2008). "Object-based target search using remotely sensed data: A case study in detecting invasive exotic Australian Pine in south Florida." *ISPRS Journal of Photogrammetry & Remote Sensing,* DOI:10.1016/j.isprsjprs.2008.04.003.

CHAPTER 3

DYNAMIC CLASS DEVELOPMENT

The research presented in Chapter 2 (the FBR HSMR solution) works of the premise that classes of interest are statically defined. The statically defined land cover classes introduce a prior knowledge to segmentation but they also restrict segmentation to the confines of these classes. For example, the land cover classes of Forest, Grass, Soil and Water do not fare very well in dense urban environments which contain many concrete/impervious features. Thus, the FBR HSMR is a good solution to the segmentation of land coverage in smaller urban environments but it can prove to be restrictive for some other types of satellite image scenes. This research is expanded in the paper presented in Chapter 4 in attempt to reduce this restriction and improve the automation of the FBR HSMR.

In the following chapter, an experiment is presented to augment the FBR HSMR solution to one that dynamically estimates the classes in a given image based on a set of features. The features for class development can be any localized measure on a given pixel (i.e. intensity, red value, etc). Fuzzy Adaptive Resonance Theory (ART) is employed to cluster these measurements into a set of classes automatically. This self organizing clustering mechanism allows the classes in the image to be estimated dynamically. When the clustering conditions change (i.e. Fuzzy ART uses a different feature set), the number of determined classes is subject to change. These experiments were performed in the hopes of further automating the FBR HSMR processes and reducing the restrictions of the statically defined land cover classes.

CHAPTER 4

REGION BASED SEGMENTATION OF QUICKBIRD IMAGERY THROUGH FUZZY INTEGRATION

This chapter contains a conference paper which was originally published as:

Wuest, B., and Y. Zhang (2008). "Region Based Segmentation of QuickBird Multispectral Imagery through Fuzzy Integration." Proceedings of the *ISPRS XXI Congress*, Beijing, China, 3-11 July, pp. 491-496.

The first author developed the algorithm and methodologies for the research presented in this paper. The second author gave advice on structuring the paper. For the sake of clarity, the paper included in this chapter has been slightly edited.

Abstract

The automatic segmentation of land cover features, within very high resolution (VHR) satellite imagery, is a complex task which is important to geo-spatial applications such as urban planning, crop monitoring and change detection. The dynamic grey-value variety of VHR imagery, along with environmental interference factors, such as cloud cover and poor lighting, impede the automation of land cover segmentation. The Fuzzy Band Ratio Hierarchical Split Merge Refinement (FBR HSMR) algorithm [Wuest and Zhang, 2008] presents a successful method for land cover segmentation through well known Band Ratios and Fuzzy Logic based comparison measures using the region-based Hierarchical Split Merge Refinement (HSMR) algorithmic framework. This paper is the

presentation of an attempt to improve the automation of the FBR HSMR. In this approach, class development for region description and comparison is dynamically determined in contrast to static class development through Band Ratios. Fuzzy Adaptive Resonance Theory (ART) is employed for dynamic class development because of its unsupervised self-organizing capabilities and ability to estimate classes without initial estimates. In addition, users can control input to class development through input vector type selection. It is hypothesized that this approach will: i) improve the automation of the FBR HSMR segmentation methodology; and ii) expand the capabilities of the FBR HSMR to provide land cover segmentation to a wider range of satellite image scenes.

4.1 Introduction

The Fuzzy Band Ratio (FBR) HSMR, presented in Wuest and Zhang [2008], introduces a prior knowledge to land cover segmentation through five statically defined land cover classes: i) Forest, ii) Grass, iii) Water, iv) Soil and v) Urban. Through Band Ratios, the FBR HSMR segmentation method identifies pixels in a given image that potentially belong to these land cover classes. This information then guides segmentation to form image segments that are either homogeneous to one of these classes or a mix of two or more of these classes. For instance, a suburb bordering a large patch of forest would be identified as a region because of its consistent mixture of grass, soil and urban while the large patch of forest would be identified as another region.

The FBR HSMR employs the HSMR algorithm framework as a basis for segmentation. The HSMR algorithmic framework is one of many region based segmentation methods that have been the focus of segmentation research of VHR imagery due to their close relationship with the object oriented paradigm. Region based methods, such as the HSMR algorithmic framework, are dependent on methods for describing regions and comparing similarity between image regions [Schiewe, 2002]. Regions can be described by a single feature like color, texture, and shape or by a combination of features. Region comparison is a method by which the descriptions of two regions are compared mathematically. An example of an adaptive method for combining features for region comparison and description is presented in Hu et al. [2005].

Image regions, in the FBR HSMR, are described by the density of the statically defined land cover classes. A Fuzzy Logic system provides a means for region comparison. Although the FBR HSMR introduces a prior knowledge of image content to image segmentation, it enforces a restriction/dependency that the static land cover classes exist in a given image and conform to the Band Ratio based function conditions defined for each class. In this paper, the restriction/dependency enforced by the statically defined land cover classes is the subject of improvement. The approach introduces dynamic class approximation to the FBR HSMR using Fuzzy ART. The introduction of dynamic class determination is expected to allow segmentation to involve more classes than the FBR

HSMR and therefore introduce more flexibility into the land cover segmentation methodology. It is hypothesized that this approach will improve the automation of the FBR HSMR methodology and produce successful land cover segmentation on a wider range of satellite image scenes.

4.2 Background

4.2.1 Hierarchical Split Merge Refinement (HSMR)

The Hierarchical Split Merge Refinement (HSMR) algorithmic framework is a region based approach to unsupervised image segmentation. As portrayed in Figure 1, this algorithmic framework performs a three-step process of: i) splitting; ii) merging; and iii) refining image segments. For a more complete description of these processes, readers can refer to Ojala and Pietikainen [1999]. The HSMR algorithmic framework is dependent on a method of describing and comparing image regions. In this approach, the methods developed by Wuest and Zhang [2008] for region description and comparison are employed for HMSR integration.

Figure 4.1: The three essential HSMR processes: (i) Hierarchical Splitting, (ii) Agglomerative Merging and (iii) Localized Pixel Refinement

4.2.2 Region Description and Comparison

As previously noted, the FBR HSMR detects information corresponding to a fixed set of land cover classes for every input image. In this approach the conditions for class development and the number of classes are dynamic. Thus, the calculations change slightly. In this section, the minor changes to the region description equations of Wuest and Zhang [2008] are detailed along with a short review of the important inputs to Fuzzy-based region comparison.

4.2.2.1 Region Description through Class Density

Class density for a class *c* in a region *R* is defined as the percentage of pixels in *R* that belong to class *c* (see Equation (4.1)).

$$d(c,R) = \left\{ \sum_{i=1}^{M} \sum_{j=1}^{N} (C_{MAP}(i,j) == c) \right\} \Big/ area(R) \tag{4.1}$$

In Equation (4.1), the == operator tests to see if the value in the produced class map (C_{MAP}) at the given position is equal to the given class index c and will return 1 or 0. The class map details are discussed in section 3. As a result, the equation sums the number of pixels in region *R* belonging to class c over the area of region *R* to give the density of class c in region *R*. A density vector for a given region *R* is formed by combining the densities of all classes. (see Equation (4.2)).

$$CDV(R) = \{d(c_1, R), \ldots, d(c_{NC}, R)\} \tag{4.2}$$

In Equation (4.2), it is shown that the class density vector (CDV) is dynamically sized to the number of class (NC).

4.2.2.2 Fuzzy Based Region Comparison

A Fuzzy Logic system for region comparison [Wuest and Zhang, 2008] compares regions to evaluate high similarity in region pairs with similar common class density and a low similarity to region pairs with a high difference in class density. The critical inputs to their Fuzzy based region comparison are Common Density (CD) and Difference in

Density (DD). These are shown in Equations (4.3) and (4.4) below [Wuest and Zhang, 2008].

$$CD(R_a, R_b) = \sum_{i=1}^{N} CDV(R_a)_i \wedge CDV(R_b)_i \tag{4.3}$$

In Equation (4.3), R_a and R_b are the image regions being compared. The fuzzy min intersection operator is applied to each element of the class density vectors from each image region and the results are summed to obtain a total common density.

$$DD(R_a, R_b) = \left\| CDV(R_a) - CDV(R_b) \right\| \tag{4.4}$$

Equation (4.4) is the Euclidean distance between the class density vectors (CDV) of the two regions in question. It represents the difference in class density between two given regions. For more details regarding the Fuzzy Logic system for region comparison, readers can refer to Wuest and Zhang [2008].

4.2.3 Fuzzy Adaptive Resonance Theory (ART)

Fuzzy Adaptive Resonance Theory (ART) provides a foundation for which all descriptive measurements on regions are calculated. Fuzzy ART is an expansion of the first Adaptive Resonance Theory (ART-1) introduced in 1976 [Carpenter et al., 1992]. It provides the ability to categorize analog input patterns using the MIN operator $(\wedge)$ of fuzzy set theory [Carpenter et al. 1991]. The appealing nature of this approach is the minimal user input to the algorithm. The algorithm relies on a few parameters, the most significant of those being the vigilance (ρ) parameter. Vigilance (ρ) governs the resulting number of classes. A high ρ value will result in a large number of fine classes, while a low ρ will result in a small number of broad classes.

4.3 Proposed Approach

In the proposed approach, Fuzzy ART organizes the image into a set of classes using a selected input vector type (v_t). The selection of v_t is user determined and, as indicated in Figure 4.2, is the first step of this approach. The selection of v_t also decides, as will be discussed in 4.3.1, the type of measurement vector for the unsupervised clustering provided by Fuzzy ART. Once a set of input vectors based on the chosen v_t is produced, clustering is performed. In the second step, a class map is produced from the Fuzzy ART clustering result. As detailed previously in Equation (4.1), the class map is an essential component to calculating region class densities. The last steps to this approach are executed according to the FBR HSMR methodology in which image regions are split, merged and refined according to their class density properties. Ultimately, the results of this approach are highly dependent upon the clustering result of Fuzzy ART.

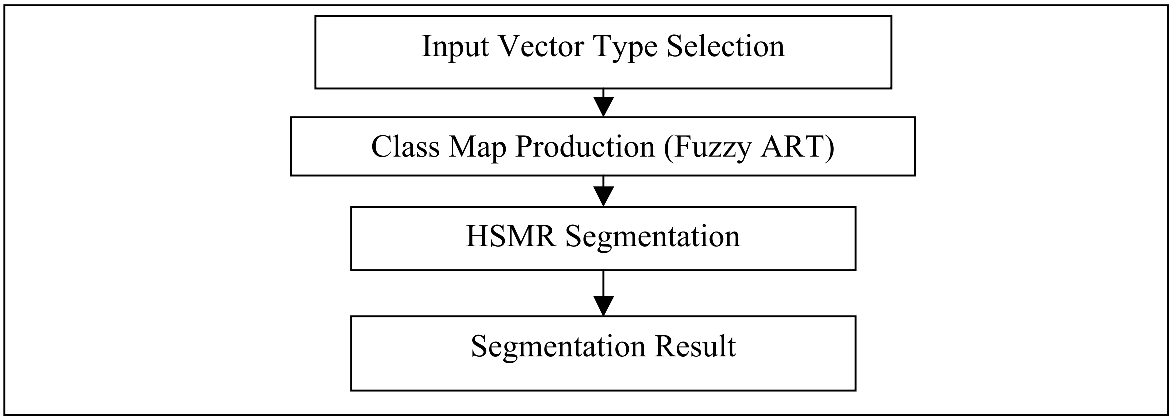

Figure 4.2: Overview of Proposed Approach

4.3.1 Input Vector Type Selection

In detail, the Input Vector Type (v_t) decides which pixel based measurements are made on a given input image. There are numerous pixel based measurements such as color, intensity, and texture features for pixels. The v_t options chosen for this study, are detailed in Table 4.1. The experimentation did include other input vector types but, due to the scope of this paper, only the following (see Table 4.1) are discussed.

A Vigilance (ρ) is part of the selection of v_t. The setting of ρ is dependent upon the size and distribution of v_t. As indicated in section 4.2.3, ρ controls the size and the granularity of the resulting class set. More details on the selection process of v_t and ρ are presented in section 4.1.

Table 4.1: Input Vector Type (v_t) Options

Input Vector Type (v_t)	**Description**
{r,g,b}	Visual Color Bands (Red,Green,Blue)
{r,g,b,nir}	All available MS Bands (Red,Green,Blue,Near Infrared)
{i}	Average Intensity $(r+g+b)/3.0$
{hue}	Hue
{pca1}	Principle Component 1
{pca2}	Principle Component 2
{pca1,pca2}	Principle Component 1 and 2

4.3.2 Class Map Production

The Fuzzy Adaptive Resonance Theory (ART) clustering algorithm provides an unsupervised method to reduce an input image into a set of classes according to the input vectors. Each pixel in the input image is assigned to a class. In this approach, a class map (C_{MAP}) is defined as a matrix of equal dimensions to the image in question. Each entry is a class index assignment for each pixel in the given image. As indicated in Equation (4.1), the class map is an integral component to the class density calculation. It is important to note that there can only be one class assignment per pixel.

4.3.3 HSMR Segmentation

The region description methods (see section 4.2.2) and the Fuzzy logic systems presented in Wuest and Zhang [2008] are integrated with the HSMR algorithmic segmentation framework to perform image segmentation. Readers can refer to Wuest and Zhang [2008] for further understanding of these methods. Using the given properties for region description and comparison HSMR processes are able to split, merge, and refine a given image into a set of image segments according to the distribution of classes within the input image. Accordingly, the final segmentation result is dependent upon the input to the Fuzzy ART component of this approach. This will be further discussed in section 4.4.3.

4.4 Experiments

These experiments utilized QuickBird MS 2.44m imagery having a size of 512 x 512 pixels. Many images were selected to include a variety of land cover scenes. A representative sample of these scenes is presented in Figure 4.3. Image size was selected in accordance with memory limitations on the Fuzzy ART and HSMR algorithms developed in C++. The Fuzzy ART and the HSMR algorithmic framework were developed according to the specifications in Carpenter et al. [1991] and Ojala and Pietikainen [1999] respectively. All measurements, with the exception of Principle

Component Analysis (PCA), are performed by algorithms developed in C++. PCA analysis is performed in PCI *Geomatica Focus*.

These experiments tested (v_t, ρ) input pairs in attempt to find one pair that would consistently provide desirable land cover segmentation results and thus improve the automation of the existing FBR HSMR method. The initial focus of these experiments was to emulate the current FBR HSMR segmentation. In this sense, determine whether Fuzzy ART could dynamically produce classes in imagery similar to that of the FBR HSMR methodology and replicate the segmentation results. If this was successful, the experiments would test other imagery to see if the dynamic class development could expand the flexibility of the FBR HSMR.

4.4.1 Fuzzy ART Parameters

Fuzzy ART clustering is controlled by a number of parameters. With respect to time performance, the Fuzzy ART clustering was set up with "One Shot Fast Learning", described in Carpenter et al. [1991]. In this type of Fuzzy ART clustering, the algorithm has its learning rate (β) set to 1.0 and its choice parameter (α) set to close to 0. In this fashion the clustering algorithm is said to be in a conservative limit and recoding is minimized [Carpenter et al. 1991]. All input vectors were normalized to the range [0, 1] using the minimum and maximum range of each attribute. They were also complement coded to prevent class proliferation. For more details, readers can refer to Carpenter et al.

[1991]. It is important to note that the performance of the Fuzzy ART algorithm in modes other than this can be quite time consuming. This, of course, is also dependant on the size of the given input image.

The setting of the (v_t, ρ) parameter pair were the subject of empirical investigations. The choice of v_t was initially made by inspecting resulting classes found when different v_t were applied to various scenes. The clustering result, for a given v_t, was compared visually to classes produced by the FBR HSMR. Through empirical investigation, it was found that the visual color bands (r, g, b) with or without the near-infrared band could approximately emulate the class development provided by the band ratio based approach. This was dependent, however, on the land cover content in the given image and is further discussed in 4.4.3. Other v_t options were chosen to test their ability to detect land cover classes. For all v_t options, it was empirically determined that the Vigilance (ρ) must be set differently for the optimal segmentation results. These observations are presented below in Table 4.2.

4.4.2 HSMR Parameters

The HSMR algorithmic framework, outlined by Ojala and Pietikainen [1999], is controlled by a number of parameters. For consistency, we will detail the parameters used by this experimentation (see Table 4.3). It is important to note that these parameters did not change for any of the presented segmentation results. It is also noted that the

HSMR modifications proposed by Wuest and Zhang [2008] were part of this experimentation. For more details on HSMR parameters and their effects on image segmentation, readers can refer to Ojala and Pietikainen [1999].

Table 4.2: Vigilance (ρ) by Input Vector Type (v_t)

Input Vector Type (v_t)	**Vigilance** (ρ)
{r,g,b}	0.98
{r,g,b,nir}	0.92
{i}	0.98
{hue}	0.98
{pca1}	0.95
{pca2}	0.95
{pca1,pca2}	0.95

Table 4.3: HSMR Parameters

Parameter	**Value**
Splitting Threshold	1.1
S Max	64
S Min	8
Merging Stop Threshold	0.98
Refinement Window Size	5

4.4.3 QuickBird 2.44m MS Image Segmentation

The experiments performed with the QuickBird 2.44m MS imagery for this paper found that, for any given image, a (v_t, ρ) pair can be found that produces a desirable land cover segmentation solution. This empirical search process for an optimal (v_t, ρ) pair can be very time consuming. However, once an optimal (v_t, ρ) pair is determined, results are comparable to the original FBR HSMR approach. A (v_t, ρ) pair could not be isolated that produced desirable segmentation results in all test images.

Successful segmentations results are displayed in Figure 4.3. Figure 4.3.a and 4.3.b show segmentation of urban scenes using all available multi-spectral bands and only visual color bands respectively. Figure 4.3.c illustrates the results of using PCA1 and PCA2 clustering on the San Francisco downtown. Figure 4.3.d shows segmentation of a suburban scene using the intensity vector type.

(a) $\rho = 0.92 \quad v_t = (r,g,b,nir)$

(b) $\rho = 0.98 \quad v_t = (r,g,b)$

(c) $\rho = 0.95 \quad v_t = (pca1,pca2)$

(d) $\rho = 0.98 \quad v_t = (intensity)$

Figure 4.3: Region-based Segmentation of QuickBird 2.44m MS Imagery through Fuzzy Integration: (a) segmentation of an urban scene using all available multispectral bands; (b) segmentation of an urban scene using only color (r,g,b); (c) segmentation of downtown San Francisco using principle components 1 and 2 (The rectangle applied on this image relates to information in Figure 4.4); and (d) segmentation of an urban scene using intensity only.

4.4.3.1 Input Vector Type Selection

From the experimentation, it was impossible to automate which v_t should be applied in which situations for successful segmentation. Automation of that kind may or may not be possible. Even though a consistency in results was not determined, a number of observations were made between v_t selection and the land cover types found in a given image. These observations are detailed in Table 4.4. As shown in Table 4.4, it was found that scenes with no water features were estimated using either a color, color with near-infrared, or the intensity input vector. Scenes containing water features are required to include the near-infrared band in class determination. However, when the water becomes cloudy or in a heavy urban environment (i.e. Port), all input vector selections have very limited segmentation results. In an urban city environment, results are not very successful using this method due to the dynamic grey-value variety in urban features. This type of land cover content requires the most trial and error for v_t selection. However, in a suburban environment there is not as much variety and results are more successful as long as water features are not present.

Table 4.4: Image Content and Input Vector Type Options

Image Content Description	v_t **Options**
No Water Features	{r,g,b} {r,g,b,nir} {intensity}
Water Features	{r,g,b,nir}
Port Water Features	Limited Success
Urban (City)	Limited Success
Suburban Environment	{r,g,b} {r,g,b,nir} {intensity}

Figure 4.4 displays an example of some of the resulting problems with v_t selection in an image containing city features. The selection of v_t has a significant effect on the resulting segmentation. In Figure 4.4.a segmentation results are displayed using all available multi spectral bands for segmentation. As circled in the image (from top to bottom) a) part of the bridge is missed, b) part of the port is merged with the water, c) multiple shadows are extracted, and d) the large port feature becomes extracted into many polygons. As demonstrated in Figure 4.4.b, that PCA based segmentation is a better solution in this case. However, the PCA solution still contains shadows and this contributes to the limited success of this solution in urban environments (indicated in Table 4.4).

(a) v_t = (r,g,b,nir)   (b) v_t = (pca1, pca2)

Figure 4.4: Problematic images containing city features: (a) segmentation using all available bands; and (b) segmentation using Principle Components 1 and 2.

4.5 Conclusion

This paper has presented an attempt to further automate the FBR HSMR land cover segmentation solution for QuickBird MS 2.44m imagery. The proposed approach provides the ability to dynamically estimate classes of information in a given image. As indicated previously, this replaces the static class development of the FBR HSMR. As shown in the experiments section, the approach provides a flexible segmentation algorithm that allows the user to change the input parameters based on the land cover types present in any given image. This approach also inherits the benefits of having a similarity measurement that can work at small area sizes from the FBR HSMR.

The experiments, performed for this expansion, also show that this methodology does not improve the automation of the FBR HSMR because the solution requires a lot of empirical parameter searching. The empirical parameter setting is transferred from the HSMR algorithmic framework to the choice of the (v_t, ρ) input pair for Fuzzy ART clustering. The (v_t, ρ) input pair selection is more important to successful segmentation results than the actual HSMR algorithmic parameters. This is shown in the experiments section. Different scenes require different values of (v_t, ρ) while the HSMR parameters remain the same (see Table 3) to produce desirable segmentation results. A method of automatically determining (v_t, ρ) from a given image would improve the automation of this approach considerably. As indicated earlier, this may or may not be possible and could be the focus of future research.

This research, however, has increased the flexibility of the FBR HSMR approach in the respect that class development conditions can be changed by the user when undesirable segmentation results are produced. Accordingly, some suggestions of how this method can be applied successfully, based on the land cover types contained in a given image, were presented. This was not possible within the FBR HSMR and is unique to the HSMR integration presented in this paper.

Acknowledgements

The authors would like to recognize the support of DigitalGlobe® and the City of Fredericton, NB, Canada for providing the imagery for this experimentation. This research is funded by the second author's NSERC Discovery Grant.

References

Carpenter, G.A., S. Grossberg and D.B. Rosen (1991). "Fuzzy ART: Fast Stable Learning and Categorization of Analog Patterns by an Adaptive Resonance System." *Neural Networks,* Vol. 4, pp. 759-771.

Carpenter, G.A., Grossberg, S., Markuzon, N., Reynolds, J.H. and D.B. Rosen (1992). "Fuzzy ARTMAP: A Neural Network Architecture for Incremental Supervised Learning of Multidimensional Maps." *IEEE Transactions on Neural Networks*, Vol 3, No. 5, pp. 698-713.

Hu, X., C. V. Tao, and B. Prenzel (2005). "Automatic segmentation of high-resolution satellite imagery by integrating texture, intensity, and color features." *Photogrammetric Engineering and Remote Sensing*, Vol. 71, No. 12, pp. 1399-1406.

Ojala, T., and M. Pietikainen (1999). "Unsupervised texture segmentation using feature distributions." *The Journal of the Pattern Recognition Society*, Vol. 32, No. 3, pp. 477-486.

Schiewe, J (2002). "Segmentation of high-resolution remotely sensed data – concepts applications and problems." *Joint International Symposium on Geospatial Theory, Processing and Applications.* Ottawa, Canada. [Internet], cited 22 July 2008. Available in .pdf format through http:/www.definiens-imaging.com/documents/reference.htm.

Wuest, B., and Y. Zhang (2008). "Region Based Segmentation of Quickbird Multispectral Imagery through Band Ratios and Fuzzy Comparison." *ISPRS Journal of Photogrammetry and Remote Sensing.* (Accepted for publication, July, 2008)

CHAPTER 5

A SUPERVISED METHODOLOGY

All the research presented to this point has operated in an unsupervised methodology. Certain knowledge has been introduced but the user's input has been restricted to numeric parameters on the HSMR algorithm. For example, the user is required to set the appropriate Merge Threshold (MT) to decide when merging of image blocks will be stopped (examples were shown in Figure. 2.11).

It can be quite an empirical process to set this. This is an example of how an unsupervised approach can be limiting from a user's perspective. A supervised approach that can give the user a visual input parameter (i.e. the ability outline areas in the image that are considered homogenous from their perspective) could bring more benefit to the segmentation process. Therefore, the final piece of research presented in this thesis moves the HSRM algorithmic framework from an unsupervised to a supervised methodology. This requires the algorithmic processes to be augmented.

For the research presented in the Chapter 6, a considerable amount of application interface development was required to allow the user to interact with a given image. This is detailed in Appendix I. The segmentation approach was modified to allow the user to select regions of a given image as training regions. These training regions are used by the supervised solution as homogeneity indicators. The modified segmentation approach estimates homogeneity based on the user defined regions; hence the segmentation process can be conducted in a supervised fashion. Through this modification, the user's input is visual and thus allows the user to empirically test segmentation results through the selection of different training regions. This research was performed to introduce more control to the HSMR segmentation process.

CHAPTER 6

SUPERVISED REGION-BASED SEGMENTATION OF QUICKBIRD MULTISPECTRAL IMAGERY

Wuest, B., and Y. Zhang (2008), "Supervised Region Based Segmentation of QuickBird Multispectral Imagery" Proceedings of the *2008 IEEE International Geoscience & Remote Sensing Symposium (IGARSS 2008),* Boston, USA, 6-11 July.

The first author developed the algorithm and methodologies for the research presented in this paper. The second author gave advice on structuring the paper. For the sake of clarity, the paper included in this chapter has been slightly edited.

Abstract

The segmentation of very high resolution (VHR) satellite imagery *(such as DigitalGlobe® QuickBird)* is becoming increasingly important to geo-related applications. New sensors provide the ability to discriminate large scale objects (small ground objects) that were not discernable with lower resolution satellite imagery such as LandSat TM. VHR satellite images also exhibit an incredible dynamic grey-value variety. These features, among others, impede existing algorithms developed for lower resolution satellite imagery to operate within the same degree of accuracy.

This paper proposes a supervised approach to the segmentation of QuickBird multispectral imagery through the integration of the Hierarchical Split Merge Refinement

(HSMR) framework. The HSMR framework was originally developed by Ojala and Pietikainen [1999] for unsupervised segmentation of textured areas. In this approach, user identified regions are employed to guide HSMR algorithmic processes. User knowledge is brought to segmentation and it is hypothesized that this will improve stabilization in HSMR segmentation across a variety of QuickBird 2.44m Multispectral satellite image scenes and improve the control of segmentation at different scales.

6.1 Introduction

The Hierarchical Split Merge Refinement (HSMR) algorithmic framework is an unsupervised region based approach to image segmentation. The key ingredients to the algorithm are methods for describing and measuring the similarity of regions [Hu et al. 2005]. In brief, *region description* defines how a region is described mathematically. A region can be described by features such as color, texture, intensity and shape. A comprehensive discussion of features for region description is presented in Trias-Sanz [2008]. *Region comparison* is essentially how the descriptions of regions are compared to one another to evaluate their similarity. A popular approach is to calculate the correlation of a feature between two regions. The HSMR framework is also accompanied by a set of parameters that control segmentation splitting, merging and refinement processes. The setting of these parameters can be a very empirical process. For more details on these parameters, readers can refer to Ojala and Pietikainen [1999] or Chen and Chen [2002].

In this paper, the proposed supervised segmentation approach requires the user to define regions considered to be homogeneous with respect to the desired segmentation. These regions are segmentation (training) templates. These templates and a Fuzzy Logic based system are the basis for the modifications presented by this paper to the HSMR algorithmic processes necessary to perform supervised segmentation. The user defined templates are described by the same region description method employed by the HSMR algorithm. Similarity becomes a joint measurement through the likeness of two regions to the user templates in combination with likeness of two regions to each other. It is hypothesized that this will allow the user to have more control over the quality and scale of segmentation.

6.2 Background

The HSMR algorithmic framework for image segmentation consists of three fundamental processes (Figure 6.1): i) Hierarchical Splitting, ii) Agglomerative Merging and iii) Local Pixel Border Refinement [Ojala and Pietikainen, 1999]. These processes all interact with a chosen similarity measure SM that evaluates the likeness of one region to another.

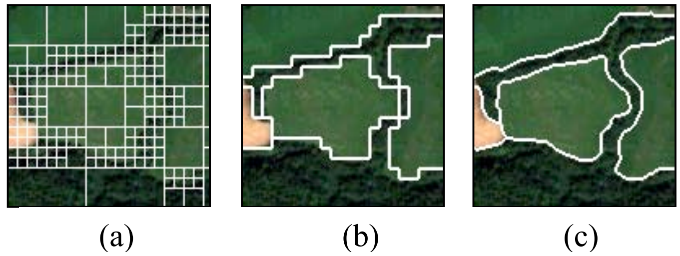

Figure 6.1: The three essential HSMR Processes: (a) Hierarchical Splitting; (b) Agglomerative Merging; and (c) Local Border Refinement. A Similarity Measure (SM) is essential to these processes.

In the first stage, an image is split into small blocks where it is evaluated as non-uniform. Agglomerative merging joins adjacent regions iteratively until an approximate (blocky) solution is determined. In the last HSMR stage segment borders are refined from blocks to delineate features properly.

6.3 Methodology

There are three key elements to the proposed supervised segmentation approach. Primarily, there are the user defined training templates (TPL). Templates are the key ingredient to augmenting the unsupervised algorithmic processes to a supervised methodology. The two other elements are a modified splitting process and a fuzzy based similarity measure that are integrated into HSMR merging and refinement decisions. An overview of this supervised approach illustrated in Figure 6.2. This section will describe how templates are defined and discuss modified algorithmic processes that bring the HSMR framework to a supervised solution.

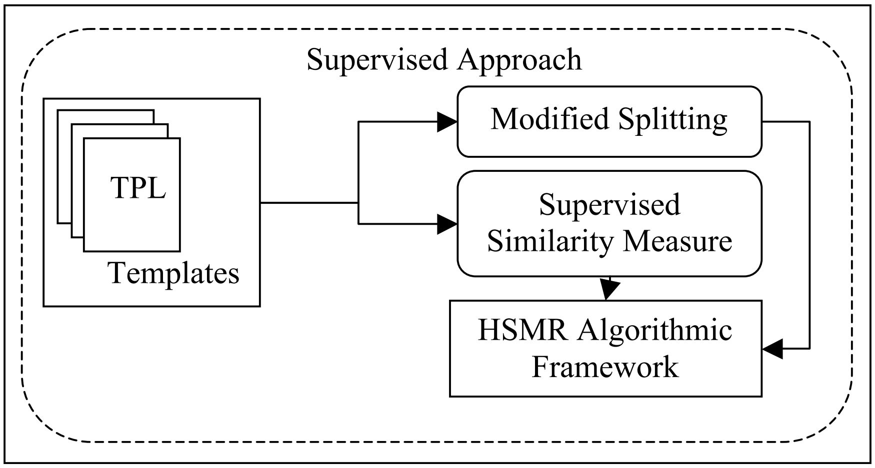

Figure 6.2: Overview of the proposed approach.

The sections below will describe how templates are defined and discuss modified algorithmic processes that bring the HSMR framework to a supervised solution.

6.3.1 User Defined Templates

The user define templates are critical to this supervised approach. These templates identify areas of the image considered as homogeneous by the user/operator. In Figure 6.3, an example is shown where the user has identified two regions of interest, [a] Forested Area and [b] Urban area. This identifies that segmentation should converge to a small scale solution for the given scene and present a land coverage segmentation. As depicted in Figure 6.3, user templates are rectangular areas of the image. They are rough approximations of information and not designed to be actually the desired segmented regions.

Figure 6.3: Examples of user defined templates. [a] Forest Area and [b] Urban Area.

6.3.2 Supervised Algorithmic Splitting

The traditional algorithm for splitting -- as presented in Ojala and Pietikainen [1999] -- is designed to measure the uniformity of an image block based on a given similarity measure SM. The algorithm splits an image from a maximum block size (S_{MAX}) down to a minimum block size (S_{MIN}). S_{MAX} and S_{MIN} are user defined parameters to the HSMR algorithm. Starting at S_{MAX}, the algorithm first quarters each block and measures six similarities ($G_1,..,G_6$) between the four adjacent child blocks. A ratio calculated through G_{MAX}/G_{MIN} is tested against a user defined split criterion threshold T. If the ratio exceeds the given threshold, the block is split into four child blocks. This process is recursively performed on the child blocks until the minimum block size (S_{MIN}) is reached or a child block is not split.

The modified splitting process uses the user defined templates $(TPL_i,...,TPL_N)$ to alter splitting decisions. The splitting threshold (T) is maintained while a template voting vector (TPL_{VOTES}) and a template score vector (TPL_{SCORES}) are added. Both vectors are equal in length to the number of templates defined by the user for segmentation. First, each of the four child blocks are compared to the user defined templates using the chosen similarity measure (SM). For each child block, the best matching template is given a vote in TPL_{VOTES}. The similarities of each child block to the given templates are accumulated in TPL_{SCORES}. The maximum number of votes handed out is four. The maximum score that a given template can be assigned is 4.0 due to the fact that the similarity measure SM is in the range [0,1]. In addition, G_{MAX} and G_{MIN} are determined from all similarity measurements made between templates and child blocks that receive a vote. From these measurements, two conditions are defined that will prevent an image block from splitting. These are displayed in Equations (6.1) and (6.2).

$$(TPL_{VOTES}(i) == 4) \text{ AND } (G_{MAX}/G_{MIN} <= T) \tag{6.1}$$

$$TPL_{SCORES}(i) >= 3.6 \tag{6.2}$$

In Equation (6.1), the condition implies that one of the user defined templates received all the votes and the user defined threshold T was not exceeded. Equation (6.2) enforces that if any template accumulates a score of 3.6 or above the image block must be considered homogeneous and not split. In all other situations the image block is split. In this fashion, splitting decisions are made with the consideration of user defined templates.

6.3.3 Supervised Merging and Refinement Measure

The merging and refinement processes, as originally defined by Ojala and Pietikainen [1999], employ the same chosen similarity measure SM from the splitting processes. The critical element to the modifications presented here is the method in which a chosen SM is combined with the user defined templates to guide merging and refinement processes. Traditionally, a SM is used to measure the similarity between two neighboring image regions. In order to incorporate the user defined templates for two given image regions (R_A, R_B), the traditional measure is defined as $S_1 = SM(R_A, R_B)$. In addition, two other measures on a user defined template TPL_i (see Equation (6.3) and Equation (6.4)) are employed.

$$S_2 = SM(R_A, TPL_i) \tag{6.3}$$

$$S_3 = SM(R_B, TPL_i) \tag{6.4}$$

S_2 is defined in Equation (6.3) as the similarity between R_A and TPL_i. S_3 is defined in Equation (6.4) as the similarity between R_B and TPL_i. These three similarity measures are incorporated into a Fuzzy Logic system to make an overall decision of the similarity between R_A and R_B.

The Supervised Similarity System (SSS) produces a fuzzy similarity measure (S_F). The model employs a variable for similarity S that is the basis of the inputs (S_1, S_2, S_3) and output S_F of the system. The universal discourse of Similarity S is defined as S = { low similarity, medium similarity, high similarity, full similarity} = {ls,ms,hs,fs} and is represented graphically in Figure 6.4. S is represented by the set of fuzzy numbers α = { (0.0, 0.0, 0.25, 0.50), (0.25, 0.50, 0.70, 0.75), (0.70, 0.75, 0.85, 0.90), (0.85, 0.90, 1.0, 1.0) }. This supervised similarity system has a total of sixty four rules $(4 \times 4 \times 4)$ and this has been condensed in Table 6.1 to four general rules.

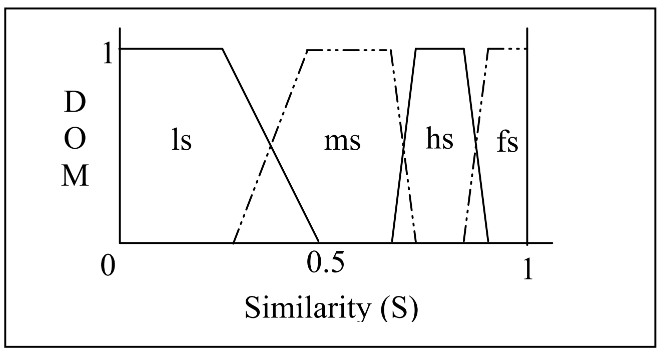

Figure 6.4: Fuzzy membership functions for input and output variable Similarity S.

As indicated previously, S_F incorporates one of the templates defined by the user into the evaluation of two given regions. In order to accommodate all of the templates, the maximum S_F produced between the two regions and all user defined templates is chosen (see Equation (6.5)).

$$S(R_A, R_B) = \max\left\{S_F(R_A, R_B, TPL_i) : i = 1, 2, \ldots N\right\} \tag{6.5}$$

Equation (6.5) is the similarity choice function on the system. For two given image regions (R_A, R_B), the supervised similarity system evaluates S_F for every template. The maximum S_F is the chosen similarity to be employed by HSMR processes for merging and refining. Through this, these processes are supervised by the user defined templates and not entirely dependent on the chosen similarity measure (SM).

Table 6.1: Supervised Similarity System (SSS) Rules

Rule	Condition
1	IF (LS_2 OR LS_3) OR (LS_1 AND ((MS_2 AND MS_3) OR (HS_2 AND MS_3) OR (MS_2 AND HS_3)) THEN LS
2	IF ((NOT LS_1) AND (MS_2 AND MS_3)) OR (LS_1 AND ((HS_2 AND HS_3) OR (MS_2 AND FS_3) OR (FS_2 AND MS_3)) OR (MS_1 AND ((HS_2 AND MS_3) OR (MS_2 AND HS_3))) THEN MS
3	IF ((NOT LS_1) AND (HS_2 AND HS_3)) OR (LS_1 AND FS_2 AND FS_3) OR ((LS_1 OR MS_1) AND ((FS_2 AND HS_3) OR (HS_2 AND FS_3))) OR ((HS_1 OR FS_1) AND ((MS_2 AND HS_3) OR (HS_2 AND MS_3))) OR ((NOT LS_1) AND ((FS_2 AND MS_3) OR (MS_2 AND FS_3))) THEN HS
4	IF ((NOT LS_1) AND FS_2 AND FS_3) OR ((HS_1 OR FS_1) AND ((FS_2 AND HS_3) OR (HS_2 AND FS_3))) THEN FS

6.4 Experiments

The experiments performed for this paper are based on an implementation in C++ developed by the primary author. The particular SM implemented for testing the supervised approach is the adaptive similarity measurement presented in Hu et al [2005]. This measurement combines color, intensity and texture features into one adaptive measurement. These experiments only tested the approach on QuickBird 2.44m MS imagery selected from a variety of different land cover environments. A number of parameters were statically set on the HSMR framework for consistency. S_{MAX} and S_{MIN} were set to 64 and 16 and the Splitting Threshold T was set to 1.1. Agglomerative merging was employed according to the specifications in Wuest and Zhang [2008] with the merge stop threshold (MST) set to 0.95. In localized pixel refinement, the window size was set to 9.

These experiments tested the feasibility of controlling the scale of segmented objects. This concept is presented graphically in Figure 6.5, where unsupervised results are presented (see Figure 6.5.b) and two different template sets are depicted (Figure 6.5.c and 6.5.d) with their corresponding results in Figure 6.5.e and Figure 6.5.f. The results in Figure 6.5.e show a very detailed segmentation of smaller objects according to the templates defined. In Figure 6.5.f the results of broader defined templates are presented. As expected the results produce a segmentation that allows a greater dynamic range of information to be included in one segment. In Figure 6.6, the results of a complicated urban scene using the proposed supervised approach are presented, in which the adaptive similarity measure defined by Hue et al. [1] was employed.

Figure 6.5: Supervised Segmentation. (a) test image; (b) unsupervised result; (c) large scale (more detail) templates; (d) small scale (less detail) templates; (e) result using large scale templates; and (f) result using small scale templates.

Figure 6.6: Result of the proposed supervised segmentation in urban area.

6.5 Discussion and Conclusions

This paper has presented a method to augment the HSMR segmentation framework from an unsupervised to a supervised methodology. The experiments have shown success through one particular similarity measure. Due to the scope of this paper, other similarity measures were not discussed. Results using this method were consistent with unsupervised results and there was considerable improvement in more complicated areas. (See Figure 6.6). This method however, still experiences difficulties with atmospheric interference especially in situations where cloud cover exists on a land/water boundary.

However, the ability to add control to segmentation does play an important part in the successes of the proposed supervised methodology.

It is concluded that this method can add more user control to segmentation. There are a number of possibilities for future research including i) developing a model for applying templates defined for one image to another image and ii) testing the application of this methodology on higher resolution imagery than that presented in this paper. The method does breed consistency to the unsupervised methodology in that definition of what is considered homogeneous in an image can be controlled more by the user. With the considerable dynamic grey value range present in today's satellite imagery, this type of control is critical.

Acknowledgements

The authors would like to recognize the support of DigitalGlobe® and the City of Fredericton, NB, Canada for providing the imagery for this experimentation. This research is funded by the second author's NSERC Discovery Grant.

References

Hu, X., Tao, C.V., and B. Prenzel (2005). "Automatic segmentation of high-resolution satellite imagery by integrating texture, intensity and color features." *Photogrammetric Engineering & Remote Sensing,* Vol. 71, No. 12, pp. 1399-1406.

Chen, K.M., and S.Y. Chen (2002). "Color texture segmentation using feature distributions," *Pattern Recognition*, Vol. 23, No. 7, pp. 755-771.

Ojala, T. and M. Pietikainen (1999). "Unsupervised texture segmentation using feature distributions," *Pattern Recognition*, Vol. 32, No. 3, pp. 477-486.

Trias-Sanz, R. Stamon, G., and J. Louchet (2008). "Using colour, texture, and hierarchical segmentation for high resolution remote sensing," *ISPRS Journal of Photogrammetry & Remote Sensing*, Vol. 63, No. 2, pp. 156-158.

Wuest, B., and Y. Zhang (2008). "Region Based Segmentation of QuickBird Multispectral Imagery through Band Ratios and Fuzzy Comparison," *ISPRS Journal of Photogrammetry & Remote Sensing*, (Accepted for publication, July, 2008).

CHAPTER 7

DISCUSSION AND CONCLUSIONS

The main objective of this research was to devise improvements in the segmentation of Very High Resolution Satellite imagery with respect to consistency, fragmentation, parameter complexity, user dependency and time complexity. This research extended the HSMR algorithmic framework for unsupervised image segmentation to achieve these goals. Through Band Ratios and Fuzzy Logic a number of improvements have been introduced to the HSMR framework and a new supervised HSMR has been presented. The conclusions and findings of the research presented in this thesis are summarized in this chapter along with recommendations for further research.

7.1 HSMR Improvements

It was demonstrated that the algorithmic modifications presented in Chapter 2 were successful in improving fragmentation and consistency in HSMR segmentation. In addition, the generic refinement improvement solves problems associated with non-contiguous and similar regions (as depicted in Figure 2.8). Fragmentation is a very prominent problem with respect to Object Oriented classification because fragmented regions are not representative of real-world objects. The merging modifications presented in section 2.3.3 demonstrate a consistency in results regardless of the Merge Importance definition applied. This modification introduces a consistency factor that has demonstrated an improvement in reducing the presence of over- and under-segmentations. This, in turn, has improved the consistency of results using the HSMR framework.

7.2 Fuzzy Band Ratio HSMR

The FBR HSMR presented in Chapter 2 introduces a unique segmentation approach in that Band Ratios are introduced to provide segmentation with a prior knowledge of image content. The Band Ratio Functions (see Table 2.2) develop five land cover classes of interest. These classes are combined into a Fuzzy Logic based system to judge the similarity of regions based on their class densities.

This approach introduces a consistency to segmentation because the same classes of interest will be retrieved every time. This certain knowledge has shown to breed some consistency to the resulting segmentations. In addition, the fuzzy logic system for judging similarity is computationally superior to other similarity measurements such as correlation. The fuzzy based similarity measure also enables the HSMR algorithm to operate at a smaller block size than other similarity measurements. This does improve the overall results of the segmentation algorithm.

Further research in this area has been identified as: 1) dynamic category/class development (addressed in Chapter 4); 2) simplification of Fuzzy System inputs; and 3) dynamic parameter selection. Another area of interest is to estimate the Band Ratio functions in imagery from other high resolution satellite sensors (such as that of Ikonos).

7.3 Fuzzy ART HSMR

The research in Chapter 4 expanded on Chapter 2 through Fuzzy Adaptive Resonance Theory (ART). This research presented experiments that were based on the recommendations for further research into dynamic class development. These experiment showed that a flexible solution was obtained that could produce successful segmentations through empirically setting the (v_t, ρ) parameter set. The drawback of this solution is that automation of the original FBR HSMR was not improved. However, the solution does give the user the flexibility to change class development conditions and achieve more desirable results. Future research could look at methods for optimal estimation of (v_t, ρ) and an alternative method to dynamic class development other than Fuzzy ART.

7.4 Supervised HSMR

A supervised HSMR solution has been developed. This solution augments all algorithmic processes to work in a supervised mode. The benefactor of this approach is the user. Regardless of the similarity measure employed, the user is given the opportunity to place further restrictions on homogeneity. This, again, provides the segmentation with prior knowledge. This solution has been tested using the adaptive similarity measure proposed by Hu et al. [2005]. The results presented are consistent with unsupervised results and were shown to allow the user to have control on the scale of resulting segmentation (see Figure 6.5). This kind of control does not exist in the unsupervised HSMR. In this solution, the parameter complexity is reduced; the user identifies regions visually and is not subjected to a set of numeric values.

This supervised HSMR has shown promise and there are a number of areas that are identified for further research. The prototype developed for this research only allows for rectangular areas. It would be more advantageous that users be able to define polygons rather than rectangles. In addition, a model for applying the user templates from one image to another might prove to reduce the parameter complexity substantially through multiple image scenes.

Appendix I

Software Design

A considerable amount of programming was performed for this research. This research required the development of a C++ object library and user interface. This appendix outlines the details of this development for further clarification of the research presented in this thesis. The main components of the software design are the GeoTIFF library, C++ Segmentation Library and a Microsoft Foundation Class (MFC) Segmentation application. The GeoTIFF library provides functionality to the segmentation library and in turn the segmentation library provides functionality to the MFC segmentation. In addition, many console applications were written on the segmentation library for testing purposes. The structure of these developments is illustrated in Figure I.1.

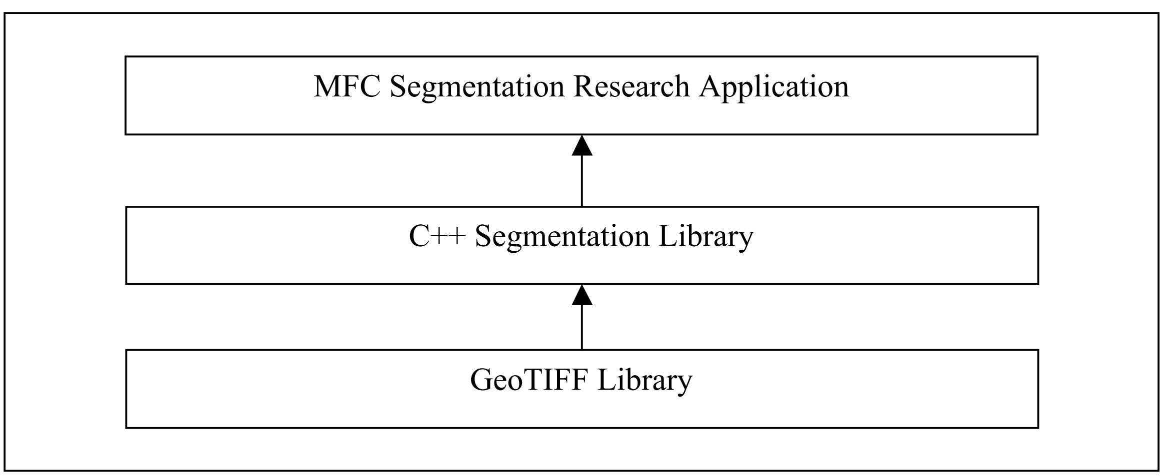

Figure I.1: Overview of C++ Development

I.1 GeoTIFF Library

The GeoTIFF library is publically free code base available at http://www.remotesensing.org/geotiff/geotiff.html. This code is the result of numerous professionals who have worked to extend the Tagged Image File Format (TIFF). This file format is a common format to image applications in remote sensing. To adhere to these standards and to simplify development, this library was integrated into this research. All results are present using the GeoTIFF image format. This appendix will not elaborate on the TIFF file format. Extensive TIFF file format information can be found at http://www.awaresystems.be/imaging/tiff.html.

I.2 C++ Segmentation Library

In a commercial environment, the C++ segmentation library should have been broken down into multiple libraries according to functionality. For research purposes, all objects were included in one big library developed using Microsoft Visual C++ 6.0. This library was developed in order to maintain small research applications and to promote code reuse. The main sections of this library are outlined in Table I.1.

Table I.1: C++ Segmentation Library Object Categories

Object Category	Description
Base Objects	Fundamental Objects for Image Processing
File Objects	File Based Objects
Processor Objects	Various Processors for Pixel Based Measures
Clustering Objects	Objects for various clustering algorithms.
Fuzzy Logic Objects	Generic Objects to develop Fuzzy Systems.
HSMR Objects	Generic HSMR Algorithm Objects
Tool Objects	Tool Objects for Segmentation and Clustering

I.2.1 Base Objects

Base objects in the segmentation library include objects for matrices, histograms, arrays and other general functionality needed for image processing. These objects are employed throughout the whole library to perform processing and measurements.

I.2.2 File Objects

The file based objects in this library are implemented for interfacing to three different file types. Two of the file interfaces were designed solely for the purpose of this research, while the other was implemented as a wrapper on the GeoTIFF library. These file interfaces are:

1. GeoTIFF File Interface
2. HSMR Segmentation Result File Interface
3. User Template File

I.2.2.1 GeoTIFF File Interface

The GeoTIFF File Interface is an object wrapper on the publicly available GeoTIFF Library. (See section I.1). These libraries are written in C and difficult to program in when using C++ objects. The interfaces in this library provide an Object Oriented method to access GeoTIFF files. This provided the ability for any research application to open, manipulate and save GeoTIFF files.

I.2.2.2 HSMR Segmentation Result File Interface

The HSMR segmentation framework, as indicated in Figure 2.2, performs segmentation in three stages (split, merge, refinement). For research purposes; it was necessary to save the segmentation result and view the results of the intermediary processes of splitting and merging at a later time. This led to the development of an HSMR file that allowed the programmer to store multiple HSMR segmentation results in a file. Each result entry contains a splitting, merging and refinement result that can later be accessed by the user. This will be demonstrated in section I.3 when the user interface is discussed.

I.2.2.3 User Template File Interface

A simple file interface was designed to store the user templates defined on an image in the supervised HSMR research (presented in Chapter 6). This enabled research to access templates already defined on a given image when testing the supervised segmentation algorithm. This file is simply a list of rectangular positions relative to the offset of the given input image.

I.2.3 Processor Objects

Various pixel based processing was necessary for the research presented in this thesis. A data processor object model was created for all the processing involved in this research. The processors for this research are listed in Table I.2.

I.2.4 Clustering Objects

The clustering objects in C++ library are simply a set of lists and objects that facilitate the clustering algorithms developed for this research. They allow the ability to add and remove cluster elements. In addition there is the flexibility to recalculate certain statistics measured on a given cluster.

I.2.5 Fuzzy Logic Objects

For the research presented in this thesis, a number of fuzzy systems were developed to test theories and possibilities. Prior to this research, a set of base objects were developed to model a generic fuzzy system. These base objects are detailed in Table I.3.

Table I.2: Fuzzy Logic Base Objects

Base Object	**Description**
Fuzzy System Object	Base object for any given Fuzzy System.
Fuzzy Variable Object	Base object for any given Fuzzy Variable.
Membership Function Object	Membership Function Base Object.

Table I.3: Processor Objects

Processor Object	Description
Forest Processor	Band Ratio Function detailed in Table 2.2 for identifying forest pixels.
Grass Processor	Band Ratio Function detailed in Table 2.2 for identifying grass pixels.
Earth Tone Processor	Band Ratio Function detailed in Table 2.2 for identifying soil pixels.
Water and Shadow Processor	Band Ratio Function detailed in Table 2.2 for identifying water and shadow pixels.
Urban Processor	Band Ratio Function detailed in Table 2.2 for identifying urban pixels.
Hue Processor	Hue calculation based on Hu et al. [2005].
Saturation Processor	Saturation calculation based on Hu et al. [2005]
Intensity Processor	Intensity calculation based on Hu et al. [2005]
Local Binary Pattern Processor	Texture measure calculation based on Ojala and Pietikainen [1997].
Channel Ratio Processor	A processor that divides any given bands to produce a ratio result.
Entropy Processor	An entropy calculation based on Equation 2.6.
Standard Deviation Processor	A simple texture processor based on the local st. dev of a given pixel.
NDVI Processor	A NDVI Processor based on Equation 2.3.

The fuzzy logic base objects are designed to work with each other to allow for fuzzy systems to be easily created. The basic concept is that a fuzzy system consists of one or more variables. In turn each variable consists of one or more membership functions. The C++ library implemented triangular, trapezoidal and linear membership functions. For more details on membership functions, readers should refer to Bojadziev and Bojadziev [1995]. Figure I.2 presents the relation between the fuzzy logic base objects to produce a generic model for creating fuzzy systems. A Fuzzy System contains one or more Fuzzy Variables. A Fuzzy Variable contains one or more Membership Functions. A Membership Functions may belong to zero or many Fuzzy Variables.

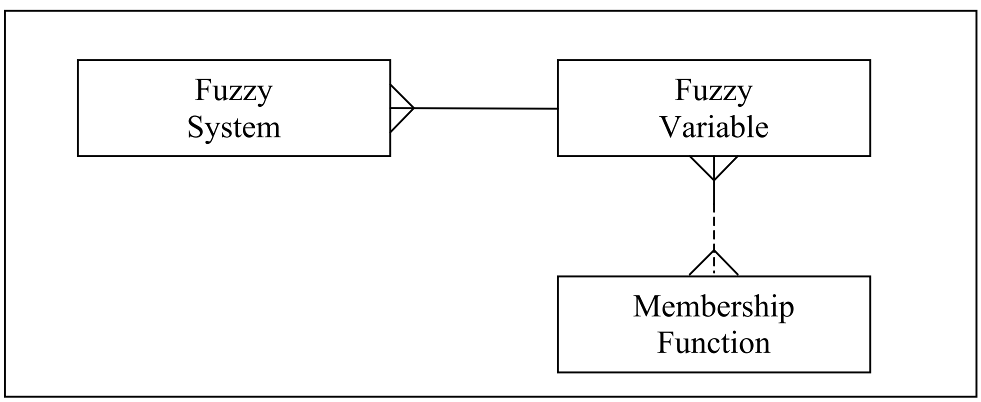

Figure I.2: Fuzzy Object Relational Model

I.2.6 HSMR Objects

As presented in this research, the HSMR algorithmic framework involves a lot of image processing. The HSMR objects developed in the C++ segmentation library allow for the algorithmic processes to operate with different similarity measures. The processing is performed through four main object classes. These object classes are presented in Table I.4.

Table I.4: HSMR Objects

Object	Description
Image Block Tree	This is a spatial data structure designed to perform the splitting and merging elements of the HSMR algorithm.
Image Block	An image block is an element on a node of the image block tree.
Image Object	An image object contains multiple Image Blocks and is can be shared by multiple nodes on an Image Block Tree.
Object Refiner	The object refiner performs the localized border refinement of the HSMR algorithm

I.2.6.1 Image Block Tree

The Image Block Tree is a simple tree structure designed for the HSMR algorithm. It is a mixture of spatial data structures found in Samet [1999]. For the purposes of this research it was not necessary to implement the complex data structure of the RTree or QuadTree. However, it was necessary to have a data structure that could quickly determine neighbors of square features within an image and have the ability to merge them into larger objects. Because the HSMR algorithm splits an image from a maximum block size down to a given minimum block size, this tree can assume a structure in which nodes represent blocks (square feature) of the image. Figure I.3 shows an overview of the Image Block Tree structure.

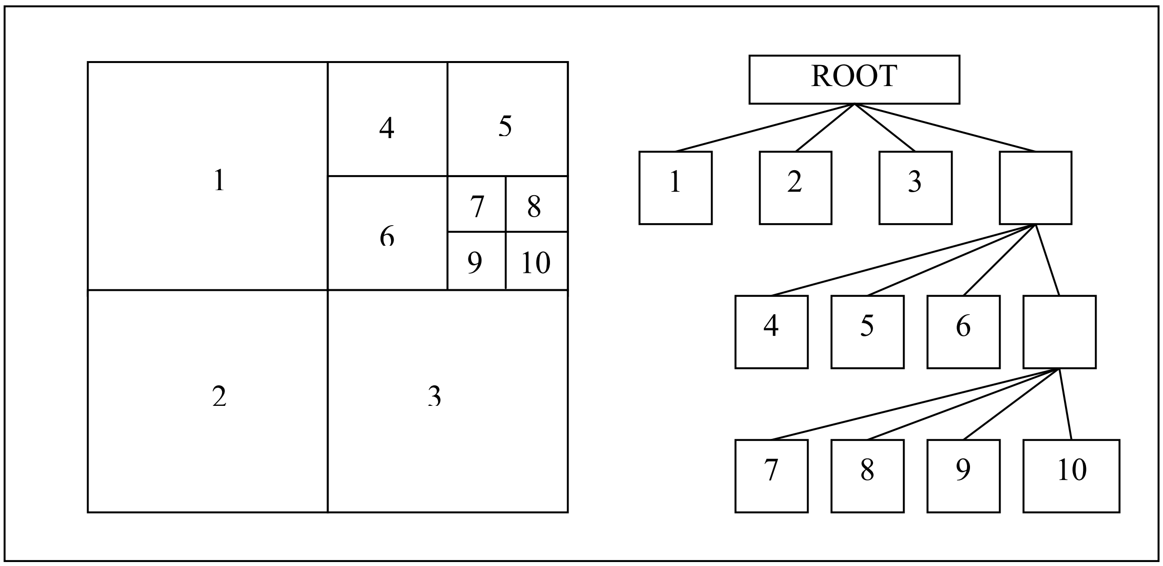

Figure I.3: Image Block Tree Overview

I.2.6.2 Image Block

All nodes on the Image Block tree that do not have children contain an image block. This image block contains the processors necessary for the measurements to be made on the type of image block. For example an image block used for FBR HSMR segmentation (presented in Chapter 2) would contain pointers to processors on the given image that implement all the Band Ratio Functions listed in Table 2.2. In this fashion, different

Image Blocks can be designed independently of objects for the HSMR algorithmic processes.

In addition, all image blocks also implement a unique method for comparing themselves to an image block of their type. This is important because different processors require different similarity measures. For example one image block type may employ a fuzzy system for similarity while another will employ a histogram based correlation measure. In this fashion the comparison measures and processors are kept separate from tree operations.

I.2.6.3 Image Objects

Image objects are objects which contain one or more image blocks and the combined data of all their contained image blocks (processor information). They store this information in an Image Block Tree. In this fashion multiple nodes can contain pointers to the same Image Object because as blocks are merged they form larger image objects. This allows neighbors of Image Blocks to be accessed quickly in the merging process of the algorithm.

I.2.6.4 Object Refiner

The Object Refiner implements the localized border refinement of the HSMR algorithm. This object is initialized from the result of a merged Image Block Tree. The results are then accumulated into a set of image objects. The iterative processing of this object inspects border pixels and moves pixels from one object to another where necessary.

I.2.7 Tool Objects

The C++ segmentation library contains two tool objects to perform the HSMR segmentation and Fuzzy ART clustering. These objects are mother objects that encapsulate all the functionality needed to perform these two tasks. They are designed to take an image and the required parameters and perform all the necessary processing. These tool objects simply development of test applications and the MFC Segmentation application presented in section I.3.

I.3 MFC Segmentation Research Application

The research application for this thesis was developed in Microsoft Visual C++ using in the MFC Document View model. The application interfaces to all three of the file interfaces discussed I.2.2. When an image is opened, the application will search the current directory for a results file (section I.2.2.2) and a template file (section I.2.2.3) with the same corresponding file prefix. A snapshot of the application is displayed in Figure I.4.

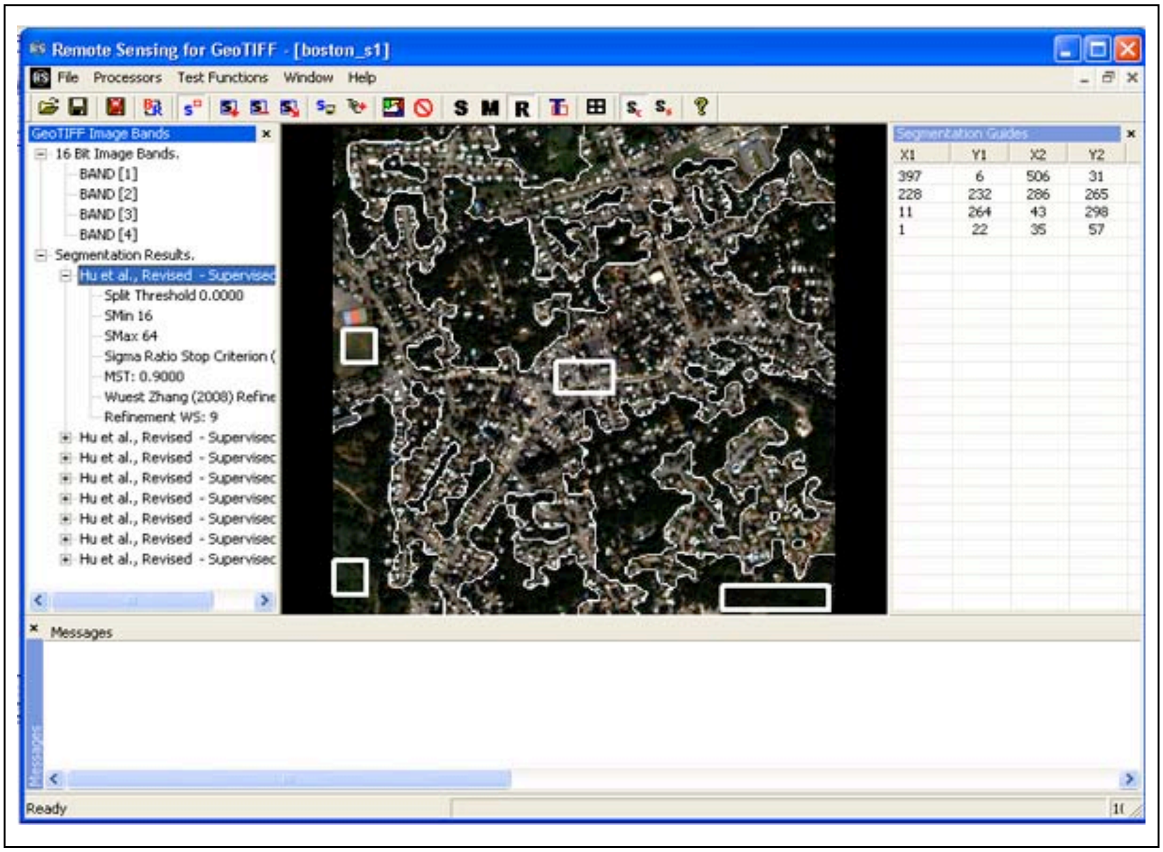

Figure I.4: Segmentation Application Interface

This application contains five main components: three panels, a tool bar and a display view. These components work together to provide the user with the functionality to test, save and export segmentation results from GeoTIFF images. These components are summarized in Table I.5.

Table I.5: Application Components

Application Component	Description
Tool Bar	This component allows the user to access all the functionality of the application.
Image Panel	This panel allows the user to access image information and segmentation results.
Segmentation Guides Panel	This panel allows the user to access the user defined templates (if any) defined on the image.
Message Panel	The message panel is used by the application to notify the user of any important information or errors associated with their application use.
Display View	The display view displays the given image with any selected overlays.

The following sections will go into the detail of the tool bar and the image panel. The other components do not require any more expansion than that displayed in Table I.5.

I.3.1 Application Toolbar

The toolbar provides the user with the ability to access all the functionality of the segmentation application. The main functionalities includes,

1. Open/Save/Export Image;
2. Add/Remove/Export User Template;
3. Perform Segmentation;
4. Delete Segmentation;
5. Turn User Template Display On/Off;
6. Turn Split, Merge, or Refinement Display On/Off; and
7. Display image with different Histogram Stretching Modes.

This section will not go into details of this functionality with the exception of the perform segmentation action. The segmentation action allows the user to perform segmentation according to any of the research presented in this thesis. The segmentation dialog is shown in Figure I.5.

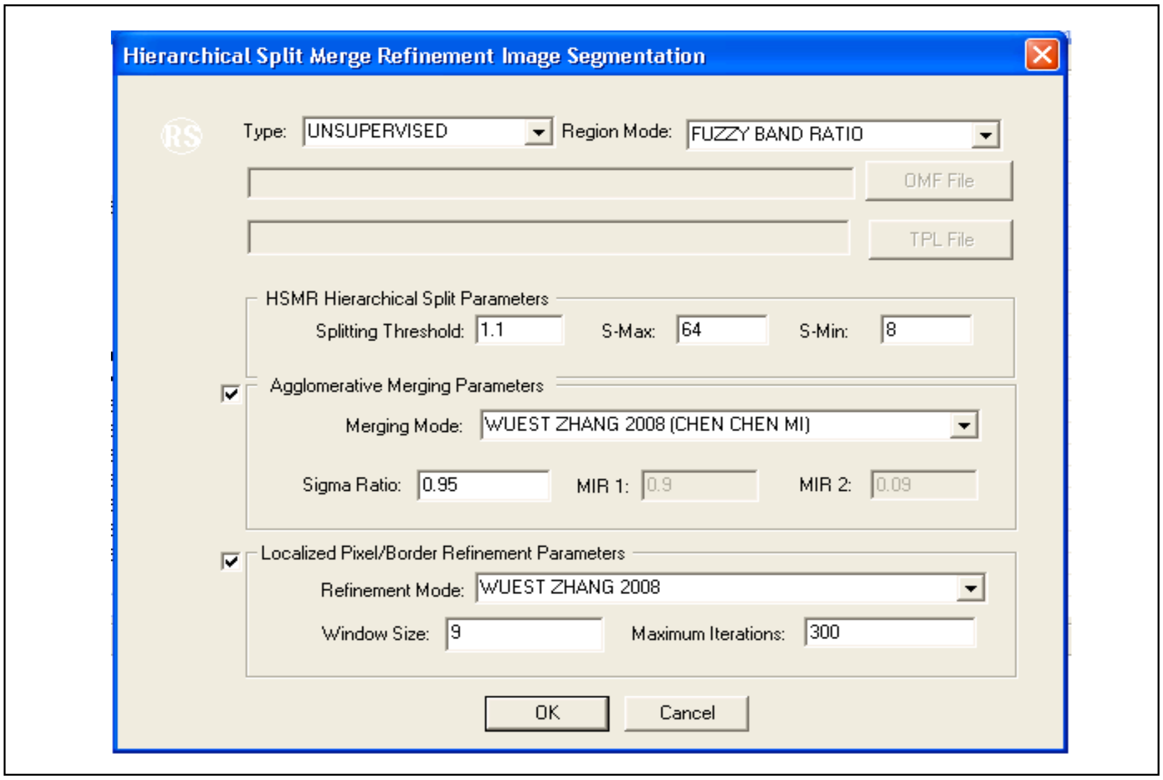

Figure I.5: Segmentation Dialog

As depicted in Figure I.5, the segmentation dialog allows the user to select and define all the required parameters to perform segmentation using the research developed for this thesis.

I.3.2 Image Panel

The Image Panel provides the user with the ability to view the band information on the given image and see the information regarding the saved segmentations for the image. The user can select a given segmentation in the panel and use the tool bar functionality (section I.3.1) to turn the displays of this segmentation on/off. The Image Panel is shown in Figure I.6.

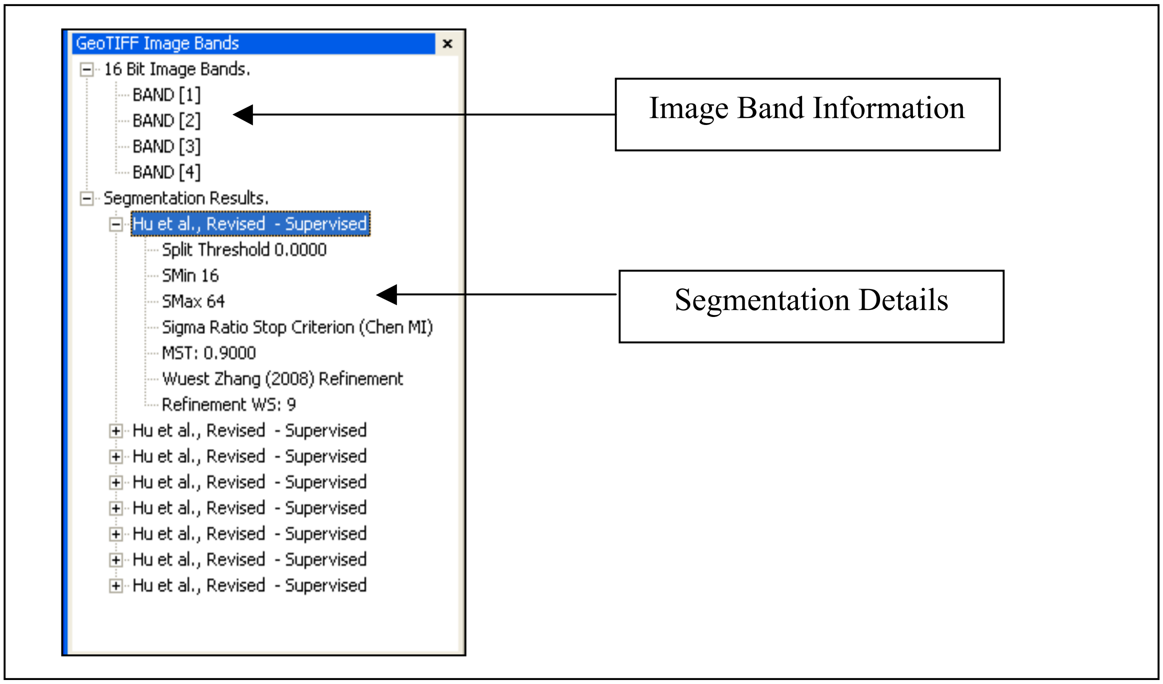

Figure I.6: Application Image Panel

References

Aitkenhead, M.J. and R. Dyer (2007). "Improving Land-cover Classification Using Recognition Threshold Neural Networks." *Photogrammetric Engineering & Remote Sensing*, Vol. 74, No. 4, pp. 413-421.

Baatz, M. and A. Schape (2000). "Multiresolution segmentation – an optimization approach for high quality multi-scale image segmentation." *Angewandte Geographische Informations-Verarbeitung XII*. Ed. J. Strobl et al. AGIT Symposium, Salzburg, Germany, 2000. pp. 12-23. [Internet], cited 22 July 2008. Available in .pdf format through http:/www.definiens-imaging.com/documents/reference.htm.

Benz, U.C., Hofmann, P., Willhauck, G., Lingenfelder, I. and M. Heynen (2004). "Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information." *ISPRS Journal of Photogrammetry & Remote Sensing*, Vol. 58, No. 3-4, pp. 239-258.

Beaulieu, J. and M. Goldberg (1989). "Hierarchy in Picture Segmentation: A Stepwise Optimization Approach." *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 11, No. 2, pp. 150-163.

Bojadziev, G. and M. Bojadziev (1995). *Fuzzy Sets, Fuzzy Logic, Applications*. World Scientific Publishing, River Edge, NJ.

Carpenter, G.A., S. Grossberg and D.B. Rosen (1991). "Fuzzy ART: Fast Stable Learning and Categorization of Analog Patterns by an Adaptive Resonance System." *Neural Networks,* Vol. 4, pp. 759-771.

Carpenter, G.A., Grossberg, S., Markuzon, N., Reynolds, J.H. and D.B. Rosen (1992). "Fuzzy ARTMAP: A Neural Network Architecture for Incremental Supervised Learning of Multidimensional Maps." *IEEE Transactions on Neural Networks*, Vol 3, No. 5, pp. 698-713..

Cha, S.H. and S.N. Srihari (2002). "On measuring the distance between histograms." *Pattern Recognition,* Vol. 35, No. 6, pp. 1355-1270.

Chen, K.M. and S.Y. Chen (2002). "Color texture segmentation using feature distributions." *Pattern Recognition Letters,* Vol. 23, No. 7, pp. 755-771.

Chen, Q., Luo, J., Heng, P.A. and D. Xia (2007). "Fast and active texture segmentation based on orientation and local variance." *Journal of Visual Communication and Image Representation,* Vol. 18, No. 2, pp. 119-129.

Cheng, H., Jiang, X.H., Sun, Y and J. Wang (2001). "Color image segmentation: advances and prospects." *Pattern Recognition,* Vol. 34, No. 12, pp. 2259-2281.

Conchedda, G., Durieux, L. and P. Mayaux (2008). "An object-based method for mapping and change analysis in mangrove ecosystems." *ISPRS Journal of Photogrammetery & Remote Sensing*, DOI:10.1016/j.isprsjprs.2008.04.002.

Fan, X., Zhang, G. and X. Xia (2008). "Performance Evaluation of SVM in Image Segmentation." *IEEE International Workshop on Semantic Computing and Applications,* Incheon, Korea, pp. 160-165.

Hay, G.J., Blaschke, T., Marceau, D.J. and A. Bouchard, (2003). "A comparison of three image-object methods for the multiscale analysis of landscape structure." *ISPRS Journal of Photogrammetry & Remote Sensing*, Vol. 57, No. 5-6, pp. 327-345.

Hagner, O. and H. Reese (2007). "A method for calibrated maximum likelihood classification of forest types." *Remote Sensing of the Environment*, Vol. 110, No. 4, pp. 438-444.

Hoppner, F., Klawonn, F., Kruse, R. and T. Runkler (1999). *Fuzzy Cluster Analysis: Methods for classification data analysis and image recognition.* John Wiley & Sons Ltd., New York, NY USA.

Hu, X., Tao, C.V. and B. Prenzel, B (2005). "Automatic segmentation of high-resolution satellite imagery by integrating texture, intensity, and color features." *Photogrammetric Engineering & Remote Sensing*, Vol. 71, No.12, pp. 1399-1406.

Liu, Y., Li, M., Mao, L. and F. Xu (2006). "Review of remotely sensed imagery classification patterns based on object oriented image analysis." *Chinese Geographical Science,* Vol.16, No. 3, pp. 282-288.

Mallinis, G., Koutsias, N., Tsakiri-Strati, M. and M. Karteris (2008). "Object-based classification using Quickbird imagery for delineating forest vegetation polygons in a Mediterranean test site." *ISPRS Journal of Photogrammetery & Remote Sensing,* Vol. 63, No. 2, pp. 237-250.

Maxwell, T and Y. Zhang (2006). "A Fuzzy Logic Approach to Supervised Segmentation for Object-Oriented Classification," *ASPRS Annual Conference*, Reno, Nevada.

Moller, M., Lymburner, L., and M. Volk (2007). "The comparison index: A tool for assessing the accuracy of image segmentation." *International Journal of Applied Earth Observation and Geoinformation*, Vol. 9, No. 3, pp. 311-321.

Navulur, K (2007). *Multispectral Image Analysis Using the Object-Oriented Paradigm*. CRC Press, Boca Raton, FL.

Ng, W.S. and C.K. Lee (1996). "Comment on Using the Uniformity Measure for Performance Measure in Image Segmentation." *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 18, No. 9, pp. 933-934.

Nichol, J. and C.M. Lee (2005). "Urban vegetation monitoring in Hong Kong using high resolution multispectral images." *International Journal of Remote Sensing*, Vol. 26, No. 5, pp. 903-918.

Ojala, T. and M. Pietikainen (1999). "Unsupervised texture segmentation using feature distributions." *Pattern Recognition,* Vol. 32, No. 3, pp. 477-486.

Ojala, T., Pietikainen, M. and D. Harwood (1996). "A comparative study of texture measures with classification based on feature distributions." *Pattern Recognition,* Vol. 29, No. 1, pp. 51-59.

Pal, N.R. and S.K. Pal (1993). "A review on image segmentation techniques." *Pattern Recognition*, Vol. 26, No. 9, pp.1277–1294.

Parker, J. (1996). *Algorithms for Image Processing and Computer Vision.* John Wiley & Sons, Inc., New York, NY USA.

Richards, J.A. and X. Jia (2006). *Remote Sensing Digital Image Analysis – 4rth Edition*. Springer-Verlag, Berlin, Germany.

Samet, H (1999). *Design and Analysis of Spatial Data Structures*. Computer Science Department, University of Maryland, College Park, Maryland, USA.

Schiewe, J (2002). "Segmentation of high-resolution remotely sensed data – concepts applications and problems." *Joint International Symposium on Geospatial Theory, Processing and Applications.* Ottawa, Canada. [Internet], cited 22 July 2008. Available in .pdf format through http:/www.definiens-imaging.com/documents/reference.htm.

Shackelford, A.K. and C.H. Davis (2003). "A hierarchical fuzzy classification approach for high-resolution multispectral data over urban areas." *IEEE Transactions on Geoscience and Remote Sensing,* Vol. 41, No. 9, pp. 1920-1932.

Shanmugam, P., Ahn, Y. and S. Shanmugam (2006). "A comparison of the classification of wetland characteristics by linear spectral mixture modeling and traditional hard classifiers on multispectral remotely sensed imagery in southern India." *Ecological Modelling*, Vol. 194, No. 4, pp. 379-394.

Shannon, C.E and W. Weaver (1949). The Mathematical Theory of Communication. The University of Illinois Press, Champaign, IL.

Tilton, J.C. (2003). "Analysis of hierarchically related image segmentations." *2003 IEEE Workshop on Advances in Techniques for Analysis of Remotely Sensed Data,* 27-28 October 2003, pp. 60-69.

Trias-Sanz, R., Stamon, G. and J. Louchet (2008). "Using colour, texture, and hierarchical segmentation for high resolution remote sensing." *ISPRS Journal of Photogrammetry & Remote Sensing*, Vol. 63, No. 2, pp. 156-168.

Tucker, C.J. (1979). "Red and photographic infra-red linear combinations for monitoring vegetation*." Remote Sensing of Environment*, Vol. 8, No. 2, pp. 127-150.

Wang, Z., and R. Boesch. (2007), "Color-and Texture-Based Image Segmentation for Improved Forest Delineation," *IEEE Transactions on Geoscience and Remote Sensing*, Vol 45, No. 10, pp. 3055-3062.

Walmsley R. (2000). *Multi-Threaded Programming in C++*. Springer-Verlag Limited, London, Great Britain.

Wuest, B., and Y. Zhang (2008). "Region Based Segmentation of QuickBird Multispectral Imagery through Band Ratios and Fuzzy Comparison," *ISPRS Journal of Photogrammetry & Remote Sensing*, (Accepted for publication, July, 2008).

Xie, Z., Roberts, C. and B. Johnson (2008). "Object-based target search using remotely sensed data: A case study in detecting invasive exotic Australian Pine in south Florida." *ISPRS Journal of Photogrammetry & Remote Sensing,* DOI:10.1016/j.isprsjprs.2008.04.003.

Vita

Candidate's full name: Ben Alexander Wuest

Universities attended:

University of New Brunswick, 1992-1997, B Sc. Computer Science

Publications:

Wuest B., and Y. Zhang (2008). "Region Based Segmentation of QuickBird Multispectral Imagery through Band Ratios and Fuzzy Comparison." *ISPRS Journal of Photogrammetry and Remote Sensing,* (Accepted for publication, July, 2008)

Wuest, B., and Y. Zhang (2008). "Region Based Segmentation of QuickBird Multispectral Imagery through Fuzzy Integration." Proceedings of the *ISPRS XXI Congress*, Beijing, China, 3-11 July, pp. 491-496.

Wuest, B., and Y. Zhang (2008). "Supervised Region Based Segmentation of QuickBird Multispectral Imagery." Proceedings of the *2008 IEEE International Geoscience & Remote Sensing Symposium,* Boston, USA, 6-11 July.

Wuest, B., Mioc, D. (2007). "Visualization and Modeling of Traffic Congestion in Urban Environments." *10th AGILE International Conference on Geographic Information Science 2007*. Aalborg University, Denmark.