A TRAINED SEGMENTATION TECHNIQUE FOR OPTIMIZATION OF OBJECT-ORIENTED CLASSIFICATION

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ABSTRACT:

Along with the significant improvement of spatial resolution of remote sensing imagery in the recent years, traditional per-pixel based classification techniques have been facing increasing problems in achieving acceptable classification results. Object-oriented classification has become a promising alternative for classifying high-resolution remote sensing imagery, such as QuickBird, Ikonos or airborne digital multispectral images. In object-oriented classification, object segmentation is a crucial process. It significantly influences the classification efficiency and accuracy. However, current state-of-the-art techniques heavily rely on the operator's experience to achieve a proper segmentation through a labour-intensive and time-consuming trail-and-error process. The accuracy of the classification is often influenced by the experience of the operator.

This paper presents a trained segmentation technique for reducing the tedious trail-and-error process of object segmentation and improving classification accuracy. A segmentation optimizer is developed based on fuzzy logic techniques, which can determine optimal object segmentation parameters to achieve a most appropriate segmentation of individual objects. Instead of trail and error, the operator just needs to apply an initial segmentation to the input image and then use the initial segments of objects of interest to train the segmentation optimizer. After the training the segmentation optimizer can then identify most suitable object segmentation parameters. Finally, these parameters are used to segment objects in the entire input image, achieving an optimal segmentation of all objects of interest.

Testing results demonstrated that the segmentation optimizer can significantly improve the process efficiency and classification accuracy, when it is integrated into a state-of-the-art object-oriented classification system.

1. INTRODUCTION

Along with increasingly available new high resolution satellite and airborne digital imagery, precise extraction of ground objects, instead of regions of certain land cover classes, has become increasingly important for a variety of remote sensing and GIS applications. However, traditional per-pixel based classification methods, such as Maximum Likelihood and Neural Networks based approaches can hardly produce satisfactory classification results for identifying individual objects, because an object in high resolution imagery is usually composed of heterogeneous pixels with different spectral attributes.

To permit automated processing of high resolution digital imagery, new methods are being developed to intelligently manage these attributes. A number of solutions for classifying high resolution imagery have been proposed, among which object-oriented classification represents a clear, logic way for automatic object extraction (Hay, *et al.* 2003). It involves the spatial pattern recognition techniques to emphasize the need for obtaining information beyond that provided in the spectral domain.

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

However, a common criticism of object-oriented image analysis is the requirement for the analyst to have significant knowledge of the land cover objects of interest and understand sensor characteristics. The analyst applies this knowledge in the selection of optimal object segmentation parameters with the aim of successfully extracting these objects (Hay, *et al.* 2003; De Kok, *et al.* 1999; Flanders, *et at.* 2003). Unfortunately, users who are familiar with the spatial and spectral behaviour of the objects and understand the underlying processing of the segmentation procedure are not always available (Flanders, *et at.* 2003).

The commercial software eCognition developed by Definiens Imaging is a state-of-the-art package for object-oriented classification, which implements the Fractal Net Evolution method in object extraction (Baatz and Schape, 1999). The general procedure of the eCognition based object-oriented classification consists of the following major steps:

(1) performing initial segmentation to generate finer primitive segments (sub-segments, which are smaller than an object and many sub-segments may form the outline of one complete object);
(2) selecting segmentation parameters to merge sub-segments within one object to form meaningful segments (each meaningful segment represents/outlines one object);
(3) building a rule base for knowledge based classification, i.e. define the rules for classifying the objects outlined by the meaningful segments into desired classes; and
(4) classifying the objects according to the meaningful segments and rule base, i.e. the segments provide the boundary information of individual objects and the rule base provide the rules to classify the objects.

In this paper we mainly focus on the second step (2) above and present a segmentation optimizer which can automatically select optimum segmentation parameters when employing the Fractal Net Evolution method. The segmentation optimizer is based on a fuzzy approach and needs to be trained using a set of initial object primitive segments. After the training the segmentation optimizer can identify most suitable object segmentation parameters. These parameters can then be used to segment objects in the entire input image, achieving an optimal segmentation of all objects of interest. Therefore, the procedure is also called fuzzy-based, supervised segmentation. Testing results have demonstrated that the supervised segmentation technique can significantly increase the speed of the selection of optimum segmentation parameters and make the process of an object-oriented classification more efficient and accurate.

2. STATE-OF-THE-ART SEGMENTATION TECHNOLOGY

The Fractal Net Evolution approach implemented by Definiens Imaging for object segmentation aims at meeting six processing goals including the: (1) production of homogeneous image object-primitives, (2) adaptability to different scales, (3) production of similar segment sizes for a chosen scale, (4) applicability to a variety of data sets, (5) reproducibility of segmentation results, and (6) requirement for reasonably fast performance (Baatz and Schape, 2000). The first three are the most important for our discussion and will be discussed in further detail during the remainder of this section.

2.1 Region merging for homogeneous object-primitives

eCognition approached the segmentation problem from the perspective of region-merging. This concept required the establishment of decision criteria in order to evaluate whether or not to merge two adjacent image objects. To accomplish the first goal above, this decision criterion was instituted with a definition of the degree of fitting between two objects based on homogeneity criteria.

To determine the degree of fitting, eCognition focused on two distinct aspects: (1) spectral heterogeneity, $h_{spectral}$, and (2) shape heterogeneity, h_{shape}. (Baatz and Schape, 2000; Definiens Imaging, 2004a). The overall spectral heterogeneity, $h_{spectral}$, is a measure of object heterogeneity change resulting from the potential merge of two adjacent objects. In this case, object heterogeneity is a function of user assigned layer weights, number of pixels comprising the objects, and standard deviation of pixel values within each layer. Similarly, the overall shape heterogeneity, h_{shape}, is based upon the change in object shape before and after the merge being considered. However, in this case object shape is described two ways: (1) compactness, and (2) smoothness. Compactness is a function of object perimeter and number of pixels within the object, whereas smoothness is a function of object perimeter and the perimeter of the object's bounding box. Together, spectral and shape heterogeneity evaluate to a single value that is indicative of the overall heterogeneity change.

This value is the so-called 'fusion' value, f, for the potential merge between two objects and is given by:

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

where w is the user assigned weight associated with shape heterogeneity (Definiens Imaging, 2004a). The merge between two objects will be considered if the fusion value falls below a user specified threshold referred to as the scale parameter. An optimization routine is applied to decide which objects should merge to minimize the total heterogeneity change.

The scale parameter is an adjustable quantity to meet the criteria for scale adaptability. The scale in eCognition is a measure of heterogeneity. As the scale increases, the region-growing algorithm will permit more merges and this allows the regions to grow larger. In this way, scale is a measure of object abstraction. It is this scale value that is ultimately compared to the fusion value to establish the stopping criteria for the region-merging process.

Finally, by employing an evenly distributed treatment order over the entire image, regions grow at a similar rate across the image. More homogenous regions will tend to grow larger as would be expected from our discussion above. However, in general, the regions can be described as similar in size for any user-defined scale.

2.2 Parameter selection for appropriate segmentation

In eCognition, with the exception of the scale parameter which must also be chosen, parameter selection involves determining the most appropriate weights for various object properties. These weights include: (1) weight associated with shape heterogeneity, (2) weight given to object compactness versus object smoothness, and (3) weight assigned to each channel in the image. See Benz et al. (2004) for detail.

To aid the user, eCognition has developed basic rules to guide the selection of segmentation parameters. In general, the segmentation should (Definiens Imaging, 2004a):

a. Employ the largest scale parameter possible while ensuring that different classes are not merged.
b. Use as much spectral information as possible while selecting enough shape to produce visually convincing results.
c. Utilize a high smoothness weight to produce objects with smooth borders while preserving the capacity to produce non-compact segments.
d. Use a large compactness weight factor to extract compact objects.

2.3 Problems in Parameter Selection

Following the above basic rules of segmentation parameter selections, a number of different segmentations must be tried until a satisfactory result is achieved. The number of combinations of the above three weights that may be applied to any given image is enormous. Further compounding this problem is a vague understanding of what result constitutes ‘satisfactory’ segmentation and how best to measure it (Zhang, 1997). Unfortunately, trial and error is inherently a very time consuming process, especially when the analyst continues to apply this approach without a clear definition by which he should cease his efforts.

3. PROPOSED APPROACH FOR PARAMETER SELECTION

3.1 Workflow of the proposed fuzzy approach

Fuzzy logic is a technology dealing with vague and imprecise input in a manner similar to human decision making (Kaehler, 1998). The imprecise nature of segmentation and selection of its associated parameters makes fuzzy logic well suited to the task of segmentation parameter determination.

The workflow for the proposed segmentation optimizer (fuzzy system) for segmentation parameter selection is shown in Figure 1. In accordance with this diagram the start state is an initial segmentation of the input image. This segmentation should be conducted using a small scale parameter with little or no weight given to the shape parameter. This results in an oversegmented image with the emphasis on spectrally homogeneous objects. In this manner small details in the image, and more importantly the land cover object of interest, are retained. Once complete, the current segmentation parameters are read into the system.

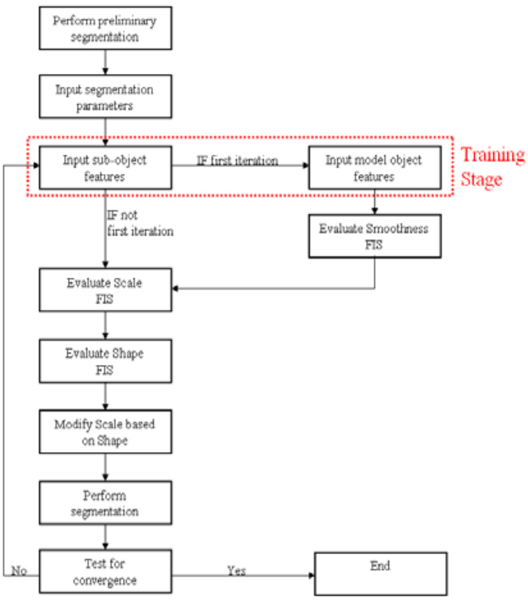

Figure 1. Proposed fuzzy segmentation parameter selection workflow

The segmentation of an input image is performed on a number of different levels to permit objects of different scales to be extracted on their own level. To define a particular land cover type, modeling of the land cover object of interest would seem the logical approach. This method is supported by Hay et al (2003) whereby they hypothesized that the “intrinsic scale of the dominant landscape objects composing a scene” should guide the selection of scale on multiple levels (Hay, *et al.* 2003). To accomplish this, the analyst should define the model in a supervised manner by selecting the sub-objects (SO) that make up the dominant landscape object of interest or model object (MO). Object features such as size, shape, tone, and texture can then be established and used to guide the segmentation process to a high quality result. The supervised selection of these objects completes the training stage.

The system will use the sub-object feature information to evaluate the current segmentation status with reference to the desired final segmentation state defined by the model object. This comparison is conceptually based on discrepancy evaluation of image object quality thereby providing the theoretical foundation for this approach (see Zhang, 1996; Zhang, 1997). By using object feature discrepancy, smoothness, scale, and shape parameters can be estimated, each using their unique fuzzy inference system (FIS) to perform this operation. Due to the interrelationship between scale and shape, the estimated scale parameter is further modified as a function of the estimated shape parameter. This is necessary since the FIS features that describe scale are purely dependent on the spectral properties of the object, yet scale is a function of both spectral and shape characteristics. Finally, segmentation is performed using the estimated parameters and convergence to the model object solution is tested based on additional feature discrepancy measures. If not yet converged, the system will continue to iterate to a solution. Therefore, convergence will only be achieved once the result is of suitable quality as determined through feature discrepancy measures between the sub-object and model object.

3.2 Fuzzy inference systems

The first step in applying the fuzzy control structure requires the definition of input features that reflect the current status of the segmentation process. In turn, these features can be used to guide the process to its successful completion. The scale FIS will be used to illustrate this process, but all FISs in the proposed system work in a similar manner.

Two fuzzy input variables are defined for the scale parameter FIS: (1) object texture, *T*, and (2) object stability, *S*. Object texture is a function of the spectral variance of pixels within the object. On the other hand, object stability is a function of the spectral mean of an object of interest, the spectral mean of its surrounding objects, and the border length shared between them. In the first case, texture, *T*, is an estimate of the spectral heterogeneity of the sub-objects comprising the final sample object. In the second case, stability, *S*, is a measure of spectral similarity of sub-objects forming the model object. Both measures are key to estimating the appropriate scale parameter. The definition of these features is an important first step in the establishment of the overall system.

The output membership functions are zero order functions (singletons) that do not move in output space. Implicating the antecedent value and the output membership functions through the fuzzy intersection operator produces a fuzzy set in output space for each rule. Using these resultant fuzzy sets and defuzzifying them through a weighted mean generates the estimated scale parameter to achieve the desired segmentation.

4. IMPLEMENTATION AND COMPARISON

4.1 Data set

Four 1000×1000 pixel subsets out of a 5000×4000 pixel Pan-Sharpened QuickBird scene of Oromocto, New Brunswick, Canada (Figure 2) were selected for the implementation and comparison in this research. The multispectral data was pan-sharpened using PCI Pansharp module to retain the detail associated with the panchromatic image layer while testing the ability of the segmentation routine to deal with the increased information content over the original multispectral imagery.

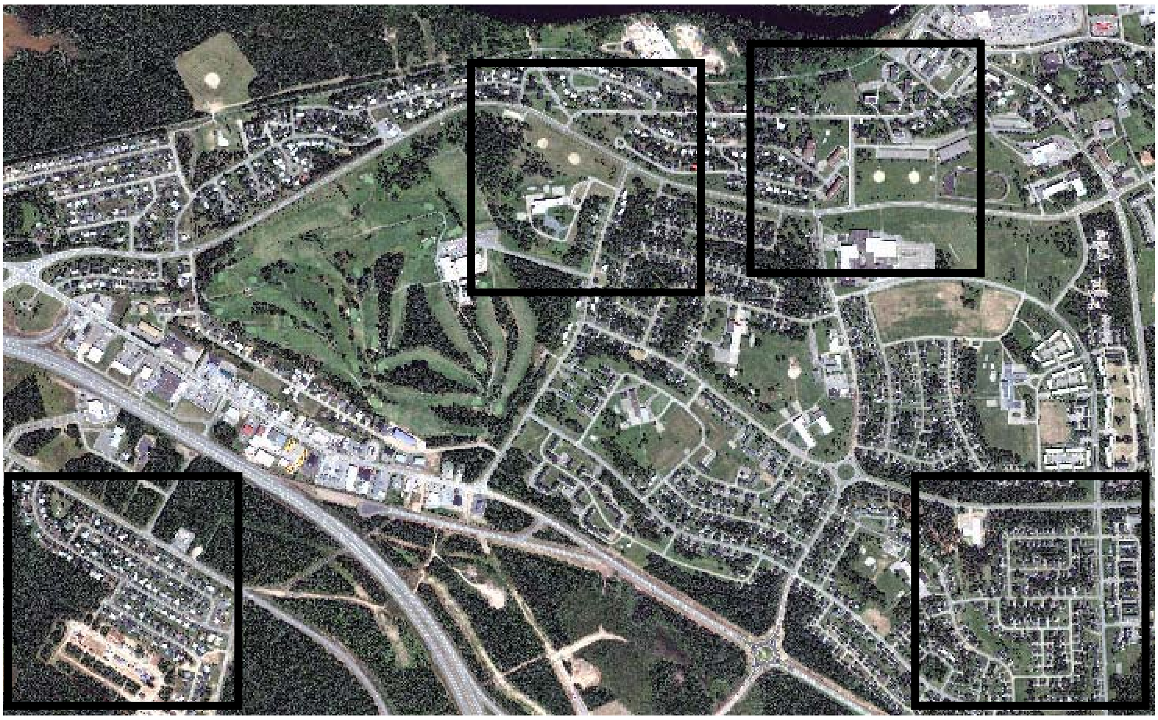

Figure 2. Overview of the study area with four subsets for performance test (Oromocto, NB, Canada)

4.2 Implementation

4.2.1 Initial segmentation: An initial segmentation was applied to the four subsets, each subset containing four pan-sharpened multispectral channels, at a finer scale to retain segment details of individual objects (Figures 3-5). These image channels were equally weighted since equal weighting of all multispectral layers should provide reasonable results for high resolution imagery in most applications (Hofmann, 2001).

To demonstrate the application of the fuzzy segmentation selection approach we focus on three separate land cover objects, each with their own unique attributes. The three land cover objects include (Figures 3-5): (1) a high contrast building, (2) a low contrast building with shadow, and (3) a tree. Each land cover object is shown with its initial segmentation completed. The sub-objects making up the final object of interest are highlighted in red.

The objects of interest are oversegmented which retains the detail of each object intact. For example, the corners of the buildings are well defined in Figures 3 and 4, the shadow can be separated from the low contrast building in Figure 4, and the tree is distinctly separated from the surrounding grass in Figure 5.

The challenge at this point is the selection of an appropriate set of segmentation parameters to permit the merging of the sub-objects to each other while preventing the merging of the sub-objects with objects belonging to other regions.

4.2.2 Segment merging through state-of-the-art technique: Without applying the proposed fuzzy approach (supervised segmentation), the selection of scale, shape and smoothness parameters is carried out by the user through a trial and error process based on the guidelines outlined in section 2.2. The segment merging results, out of initial segmentation (Figure 3-5), obtained through iterative selection and adjustment of segmentation parameters are shown in Figures 6-8.

Figures 6-8 demonstrate that the problems and successes of the trial and error approach depend on properties of the object of interest, its surroundings, user knowledge, and chance. Figure 6 shows how sub-objects can be merged with other outside regions. A similar problem occurs in Figure 7 where sub-objects comprising a low contrast building are merged with the building's shadow. Figure 8 demonstrates successful extraction of the tree but the segmentation parameters do not apply well to other nearby trees.

4.2.3 Segment merging through proposed supervised segmentation technique: When the proposed fuzzy-based supervised segmentation technique is applied to merge the initial segments (Figure 3-5), the trial and error process based on the guidelines outlined in section 2.2 can be reduced. The user just needs to train the proposed segmentation optimizer (fuzzy system) using the sub-objects making up the final object of interest, i.e. the sub-segments highlighted in red in Figure 3-5. The segmentation optimizer can then identify the optimum segmentation parameters for the segment merding, resulting in desired final object segments (Figure 9-11, red segments).

From Figures 9-11 it can be seen that employing the segmentation optimizer to segmentation parameter selection can achieves very good results. The problems outlined above in the trail and error cases have been addressed in each case.

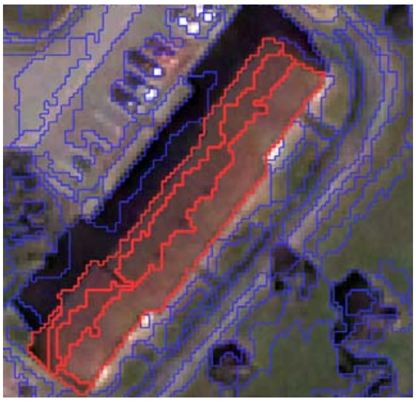

Figure 3. Initial segmentation of a high contrast building

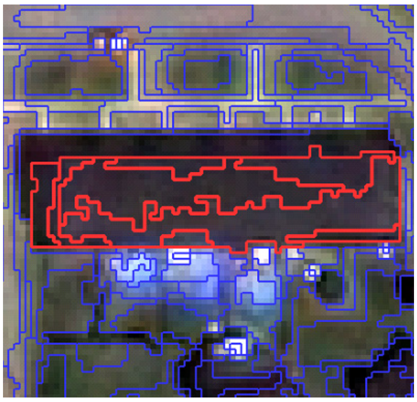

Figure 4. Initial segmentation of a low contrast building

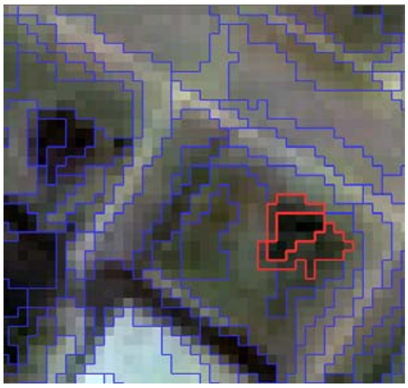

Figure 5. Initial segmentation of a tree

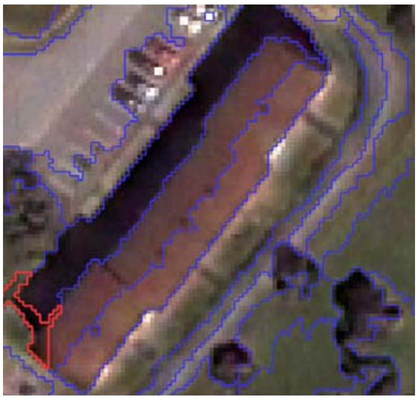

Figure 6. Sub-object of building merges with outside regions (trial and error)

Figure 7. Sub-objects of building merges with building's shadow (trial and error)

Figure 8. Successful segmentation of tree but parameters not applicable across image (trial and error)

Figure 9. Extraction of high contrast building in four iterations (proposed method)

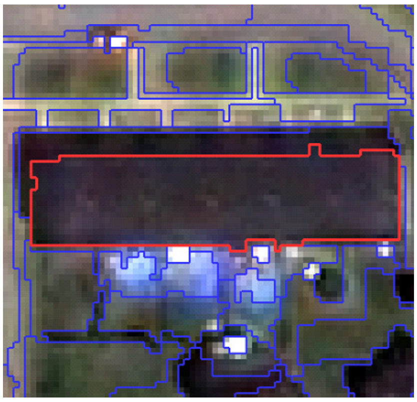

Figure 10. Extraction of low contrast building in four iterations (proposed method)

Figure 11. Extraction of tree in two iterations (proposed method)

5. DISCUSSION AND ASSESSMENT

5.1 Discussion

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

In eCognition, the segmentation of an input image is performed on a number of different levels to permit objects of different scales to be extracted on their own level. Using this approach, the fuzzy approach extracts one particular land cover type each time it is executed. By running the approach a number of times, a hierarchy of object levels can then be developed, whether creating subsequent levels using the initial segmentation or building on the results from a previous execution of the fuzzy approach.

5.2 Assessment of Results

Assessment of segmentation results can be conducted in numerous ways. This discussion will focus on qualitative analysis of the results and assess overall efficiency of the system. Definiens Imaging (2004a) suggests that human perception is a powerful assessment approach by which to measure the success of segmentation results (Definiens Imaging, 2004a). The preliminary results presented in this paper are convincing to human eye. To a large extent, shape has been maintained and only the odd pixel may appear inappropriate for the object of interest. These few pixels are a result of the initial segmentation state where pixels were grouped inappropriately for the task. These incorrect groupings were performed prior to initiating the fuzzy parameter selection approach. Although small in number, these incorrectly grouped pixels may be removed by performing the initial segmentation at a smaller scale. This will produce more objects and may permit the user to select more appropriate sub-objects.

In addition to this qualitative assessment, the proposed fuzzy approach offers the benefit of a quantitative assessment. Built around the concept of empirical discrepancy, convergence is evaluated based on specified object features. If these discrepancy measures fall within the user defined convergence threshold, then parameter selection and iteration is ceased. Using this approach, the user can have confidence that the segmentation result meets a quantitatively derived standard without the need for further evaluation.

Efficiency is a measure of effectiveness without wasting time or effort. Effectiveness in this paper is the combination of both a qualitative and quantitative assessment as discussed above. By this definition, the fuzzy approach is quite efficient since it converges near to the desired solution as defined by the user in a fast and automatic manner. The number of iterations required varies as a function of the land cover object being extracted and the initial segmentation state. However, in general the system converges in four iterations or less. By the proposed method, there is no need for a time consuming trial and error process which often forces the user to segment, assess results, delete results and segment again in an ongoing process until a convincing solution is achieved. Depending on the user's experience and understanding of underlying processes, the time taken to conduct this procedure may vary a great deal. The advantages offered by the fuzzy approach are obvious.

6. CONCLUSIONS AND RECOMMENDATIONS

"Image segmentation is one of the most critical tasks in image analysis" (Zhang, 1996). To date, eCognition's multiresolution segmentation using the Fractal Net Evolution approach has demonstrated a high degree of success in a number of applications using high resolution satellite imagery. Using this segmentation approach, the fuzzy segmentation parameter selection system proposed in this paper offers an important advantage over currently existing segmentation approaches. Through these tests, this approach demonstrates reasonable reliability, high efficiency, very good results, and excellent promise. A drawback to the fuzzy approach is the possibility for a wide variety of different membership functions and rules which can be modified to improve the system. This provides a high degree of flexibility but comes at the cost of extensive testing to establish the optimal system that is robust for a variety of data sets. Consequently, these results will provide a basis from which to continue development of the proposed fuzzy approach. In the end, a successful parameter selection methodology will promote the automatization of the object-based approach to the classification of land cover.

Further research should be conducted on other land cover objects to determine the continued reliability of the proposed system. In addition, empirical methods for segmentation evaluation such as those proposed by Zhang (1996) should be applied to further evaluate the system using other quantitative measures of segmentation success. These measures could be further confirmed through a comparison of classification accuracies resulting from employing the proposed system and the results achieved through trial and error. Finally, a controlled condition comparison between the trial and error approach and the proposed fuzzy approach would provide a quantitative measure of the efficiency of the system. With additional research and more results on a wider variety of scenes, we may truly see the advantage of this technique when incorporated into the object-oriented image analysis workflow.

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