# REGION BASED SEGMENTATION OF QUICKBIRD IMAGERY THROUGH FUZZY INTEGRATION

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**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.

## 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) Forrest, 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 a 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 for 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.

## 2. BACKGROUND

### 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

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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 1. The three essential HSMR processes: (i) Hierarchical Splitting, (ii) Agglomerative Merging, and (ii) Localized Pixel Refinement.

### 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.

**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 (1)).

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

In Equation (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 (2)).

$$CDV(R) = \{d(c_1, R), ..., d(c_{NC}, R)\} \qquad (2)$$

In Equation (2), it is shown that the class density vector (CDV) is dynamically sized to the number of class (NC).

**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 Fuzzy based region comparison, presented in Wuest and Zhang 2008, are Common Density (CD) and Difference in Density (DD). These are shown in Equations (3) and (4) below.

$$CD(R_a, R_b) = \sum_{i=1}^{N} CDV(R_a)_i \wedge CDV(R_b)_i \qquad (3)$$

In Equation (3) (Wuest and Zhang, 2008), $R_a$ 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.

$$DD(R_a, R_b) = \left\| CDV(R_a) - CDV(R_b) \right\| \qquad (4)$$

Equation (4) (Wuest and Zhang, 2008) 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.

### 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 ($\rho$) parameter. Vigilance ($\rho$) governs the resulting number of classes. A high $\rho$ value will result in a large number of fine classes, while a low $\rho$ will result in a small number of broad classes.

## 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 2, is the first step of this approach. The selection of $v_t$ also decides, as will be discussed in 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 (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.

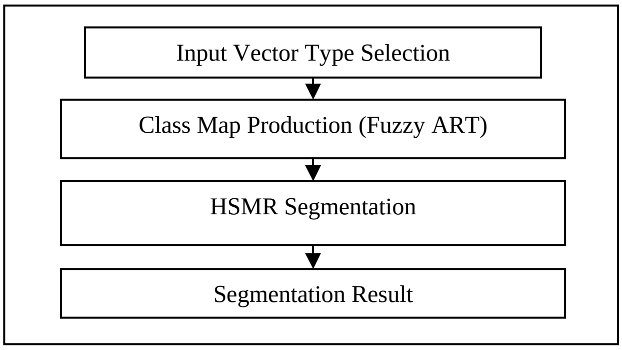


Figure 2. Overview of the Proposed Approach

### 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 1. The experimentation did include other input vector types but due to the scope of this paper, only the following (see Table 1) are discussed.

| 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 |

Table 1. Input Vector Type $(v_t)$ Options

A Vigilance $(\rho)$ is part of the selection of $v_t$. The setting of $\rho$ is dependent upon the size and distribution of $v_t$. As indicated in section 2.3, $\rho$ controls the size and the granularity of the resulting class set. More details on the selection process of $v_t$ and $\rho$ are presented in section 4.1.

### 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 (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 for a pixel.

### 3.3 HSMR Segmentation

The region description methods (see section 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 4.3.

## 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 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 $(v_t, \rho)$ 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.

### 4.1 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 ( $\beta$ ) set to 1.0 and its choice parameter ( $\alpha$ ) 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 $(v_t, \rho)$ 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 4.3. 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 $(\rho)$ must be set differently for the optimal segmentation results. These observations are presented below in Table 3.

| Input Vector Type $(v_t)$ | Vigilance $(\rho)$ |
|---|---|
| {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 2. Vigilance $(\rho)$ by Input Vector Type $(v_t)$

## 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 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.

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

Table 3. HSMR Parameters

## 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 $(v_t, \rho)$ pair can be found that produces a desirable land cover segmentation solution. This empirical search process for an optimal $(v_t, \rho)$ pair can be very time consuming. However, once an optimal $(v_t, \rho)$ pair is determined, results are comparable to the original FBR HSMR approach. A $(v_t, \rho)$ pair could not be isolated that produced desirable segmentation results in all test images.

Successful segmentations results are displayed in Figure 3. Figure 3 (i) and (ii) show segmentation of urban scenes using all available multi-spectral bands and only visual color bands respectively. Figure 3 (iii) illustrates the results of using PCA1 and PCA2 clustering on the San Francisco downtown. Figure 3 (iv) shows segmentation of a suburban scene using the intensity vector type.

**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. As shown in Table 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.

| 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 | {rg,b} {r,g,b,nir} {intensity} |

Table 4. Image Content and Input Vector Type Options

Figure 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 (i) 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 (ii), 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).

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

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

(iii) $\rho = 0.95$ $v_t$ = (pca1,pca2)

(iv) $\rho = 0.98$ $v_t$ = (intensity)

Figure 3. Region-based Segmentation of QuickBird 2.44m MS Imagery through Fuzzy Integration: (i) segmentation of an urban scene using all available multispectral bands, (ii) segmentation of an urban scene using only color (r,g,b), (iii) segmentation of downtown San Francisco using principle components 1 and 2. (The rectangle applied on this image relates to the information in Figure 4) and (iv) segmentation of an urban scene using only intensity.

(i) $v_t$ = (r,g,b,nir)    (ii) $v_t$ = (pca1, pca2)

Figure 4. Problematic images containing city features: (i) segmentation using all available bands and (ii) segmentation using Principle Components 1 and 2.

## 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 $(v_t, \rho)$ input pair for Fuzzy ART clustering. The $(v_t, \rho)$ 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 $(v_t, \rho)$ while the HSMR parameters remain the same (see Table 3) to produce desirable segmentation results. A method of automatically determining $(v_t, \rho)$ 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.

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