Fuzzy segmentation for wetland mapping: Incorporation of semivariogram texture

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ABSTRACT: Wetlands characterized by a mixing of the signatures of water, soils, and vegetations inherit the spatial vagueness in the transition zones. The fuzzy theory is applied in wetland mapping to deal with the spectral and spatial vagueness that leads to uncertain classification and indeterminate boundaries. In this paper, a newly developed semivariogram guided Fuzzy C-Means (SGFCM) clustering algorithm is proposed for wetland mapping to capture the smooth transitions. The algorithm is modified from the commonly implemented Fuzzy C-Means (FCM) clustering algorithm by adding the semivariogram texture information. The threshold defuzzifier instead of a maximum operation analyses the pixel ambiguities and describes the spatial and spectral vagueness of the transition areas. Two study sites are examined for testing the effectiveness of the SGFCM clustering algorithm. The classifications of both sites show the improvements of the overall accuracy to 86 percent and 92 percent when comparing to the results from the FCM classifier.

1 INTRODUCTION

Delineating wetland boundaries from multispectral satellite imagery is difficult because of the vagueness of the wetland definition itself (Carter et al., 1994) and of the transitional variations of ecological indicators such as hydrology, soils and vegetations. The spectral mixture of sub-pixel elements leads to an uncertainty of the classification. The binary logic used in the image classification techniques cannot give good descriptions of data that are mixed and imprecise in the nature: the spatial extent of each object can be defined ambiguously and may contain unidentified areas not belonging to the object (Burrough, 1996; Cheng and Molenaar, 1999). Fuzzy clustering, however, allows a data point to be allocated to several classes with various degrees of the given pattern. The classification can be treated more realistically when the data point is difficult to be assigned to one single class.

A commonly implemented fuzzy clustering algorithm is the Fuzzy C-Means (FCM) developed by Bezdek (1984). However, the spatial information inherited in an image is not taken into account in the clustering iterations while the image texture provides average tonal variation in various bands of an image. The semivariogram, a typically used geostatistics measure, provides the degree of spatial correlation existing between pixels (Atkinson and Lewis, 2000). It has been used to predict the optimal window sizes to be utilized in the processing of texture derivatives (Franklin et al., 1996; Chiu and Couloigner, 2004a). Miranda et al. (1998) and Chica-Olmo et al. (2000) directly add texture-derived imageries as additional input layers into the classifier, the Semivariogram Textural Classifier (STC). However, the applications using only the first lag of the variogram seem to give an incomplete picture of the variogram behaviors of ground objects.
In this paper, the standard FCM is modified to a semivariogram guided fuzzy clustering algorithm since the semivariogram of each class has a specific pattern which can adjust the segmentation results. The objective is to develop a classifier and a strategy for mapping vague wetland areas. The paper begins by briefly describing the theory of semivariogram and the modified fuzzy clustering algorithm. The proposed approach is illustrated by two case studies in the following section. Finally, the paper concludes with a discussion on the major findings of this study as well as with further research recommendations.

2 THEORY

Mathematically, the idea of FCM is to partition the data set into a given number of clusters by minimizing an objective function. While not much information about the underlying structures of the land covers is known, an assumption made in this study is that semivariograms extracted from training sites can be used as a priori knowledge to characterize the landscape structures. Therefore the proposed hybrid fuzzy clustering algorithm includes two aspects: a geospatial supervision and a spectral unsupervision.

2.1 The semivariogram

The value of each pixel can be interpreted as a regionalized variable due to its representation of the ground cell reflectance. Image samples can be used in the construction of semivariograms for remote sensing researches (Curran, 1988). The semivariogram is an unbiased description of the scale and a useful measure of the dissimilarity between spatially separate pixels (Berberoglu et al., 2000). If the value of a pixel $x_i$ is represented as $Z(x_i)$, the relation between a pair of pixels – the pixel $x_i$ and the pixel that is $h$ intervals apart (i.e. $x_{i+h}$) – can be given by the average variance of the differences between all $N(h)$ pairs. The semivariogram $\gamma(h)$ is half the per-pixel variance and can be expressed as:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_{i+h})]^2$$

(1)

where the lag distance $h$ is set to units of one side of a pixel (Figure 1). The larger $\gamma(h)$, the less similar the pixels are.

![Figure 1. Example of the semivariogram shows the parameters of nugget, sill, and range in image application.](image-url)
2.2 The Semivariogram Guided Fuzzy C-Means (SGFCM)

The objective function $J$ of the standard FCM can be specified as a sum of the distances between the feature points $x_i$ and the corresponding cluster centres $v_k$:

$$J(U, V) = \sum_{i=1}^{N} \sum_{k=1}^{C} (u_{ik})^m ||x_i - v_k||^2$$  \hspace{1cm} (2)

where $C$ is the number of classes, $N$ is the total pixels of the image, $u_{ik}$ is the partition matrix describing the degree of membership of each feature point $x_i$ belonging to the cluster $k$, and $m$ is the fuzzy index $-m = 2$ is used most of the time. The memberships $u_{ik}$ are subject to the following conditions:

$$U \left\{ u_{ik} \in [0,1] \Bigg| 0 < \sum_{k=1}^{N} u_{ik} < N \forall i \text{ and } \sum_{k=1}^{C} u_{ik} = 1 \forall k \right\}$$  \hspace{1cm} (3)

The two constraints in Eq. 3 make sure that none of the clusters is empty. So each feature point can be partitioned into no less than $C$ clusters. Moreover, they assure that every data point has the same overall weight in the data set (Bezdek, 1984).

We proposed a modification of the FCM clustering algorithm by introducing a texture component that allows the labelling of a pixel to be influenced by the semivariograms of the training sites. The semivariogram texture involves the regional homogeneity of the observations. A $s \times s$ pixel region surrounding each pixel $x_i$ to be classified is extracted from the image for a semivariogram computation. $s$, in this instance, has the same size than the one used for the training sites. For each changing lag $h$, the average distance is computed between the semivariogram for the extracted region $\gamma_i(h)$ and the semivariogram for each of the training classes $\gamma_k(h)$. Our modified objective function can be then written as:

$$J_m(U, V) = \sum_{i=1}^{N} \sum_{k=1}^{C} (u_{ik})^m \left[ ||x_i - v_k||^2 + \frac{1}{s-1} \sum_{h=1}^{s-1} ||\gamma_i(h) - \gamma_k(h)||^2 \right]$$  \hspace{1cm} (4)

Regarding the distributions of the data set, the Euclidean distance gives good results only when all clusters are spheroids of same size or when all clusters are well separated (Krishnapuram and Kim, 1999). In this study, the Mahalanobis distance replaces the Euclidean metric and guides the clustering process toward the establishment of hyper-ellipsoidal forms in the feature space.

An optimal FCM partition is obtained when the objective function is minimized through iterative convergence procedures until the change in the memberships drops below a given threshold $\varepsilon$. The modified objective function $J_m$ is solved while enforcing the constraints in Eq. 3 by means of Lagrange multipliers. The iterative procedures repeatedly update the membership functions and the cluster centres using the following equations:

$$u_{ik} = \frac{\sum_{j=1}^{N} \left[ \frac{||x_i - v_k||^2 + \frac{1}{s-1} \sum_{h=1}^{s-1} ||\gamma_j(h) - \gamma_k(h)||^2}{||x_j - v_k||^2 + \frac{1}{s-1} \sum_{h=1}^{s-1} ||\gamma_j(h) - \gamma_k(h)||^2} \right]^{-\frac{1}{m-1}}}{\sum_{j=1}^{N} (u_{jk})^m}$$  \hspace{1cm} (5)

and

$$v_k = \frac{\sum_{i=1}^{N} (u_{ik})^m x_i}{\sum_{i=1}^{N} (u_{ik})^m}$$  \hspace{1cm} (6)
2.3 **Threshold defuzzification**

The maximum operation is the common defuzzification method for the partition matrix $U$ in classification. However, such hard defuzzification does not consider the relative strength of the memberships for other classes. It assigns a pixel into a class without taking the coexisting classes into consideration at all and classification error is then committed. To address the vagueness in the transition zones, a threshold model has been developed for defuzzification. A lower and an upper threshold are given according to the maximum ambiguity. The maximum ambiguity of each pixel’s membership to any class is $1/C$. Any pixel having a membership value lower than $1/C$ will not be assigned to the associated class, whereas a pixel will be assigned to a certain class only when the associated membership value is higher than $(1 - 1/C)$ or the associated membership value is the only one larger than the lowest threshold. The ambiguous pixels can be expressed according to their membership values as follow:

$$\frac{1}{C} \leq (\mu_{ik})_{\text{ambiguity}} < (1 - \frac{1}{C}) \quad (7)$$

Those ambiguous pixels will be rejected to create new “transition classes”. For example, if the given number of classes is three, the maximum class number after clustering will be seven or lower (i.e. $2^3 - 1 = 7$). This approach allows us to capture the transition areas.

3 **METHODS**

3.1 **Image data pre-processing**

The study area is located within the boundaries of Prince Albert National Park in Northern Saskatchewan, Canada. Aspen on the uplands, jack pine on minor ridges, and black spruce in the lower poorly drained sites characterize the site. Due to local wet sites some small (10-30m) holes occur in the canopy. Two subsets of 200 by 200 pixels of a Landsat ETM+ image acquired in August 1999 over our study area are shown in Figure 2. The images are Universal Transverse Mercator (UTM) projected under Zone 13 and resampled to 25m spatial resolution.

![Figure 2. The study site is located in the southern area of the Prince. Two subsets of Landsat ETM+ image are displayed in color composite TM432. Three training sites for deriving semivariogram are shown: deciduous forest, wetland, and mixed stand.](image)

A $3 \times 3$ median filter is applied to the image to remove any noise. Raw digital numbers are converted to at-satellite reflectances according to Landsat 7 Users Handbook (Irish, 2000). Pure water bodies are excluded in the fuzzy clustering algorithm according to the map derived from Green band adjusted Normalized Difference Water Index (NDWI). An at-satellite reflectance based tasseled cap transformation is applied to decompose the multispectral images into three-dimensions: brightness, greenness, and wetness (Huang et al., 2001). The brightness, greenness and wetness
indices highlighting feature classes such as soil, vegetation, and water are used in this study as the fuzzy inputs.

Excluding water bodies, three main land cover types are used for the fuzzy clustering: deciduous forest, wetland, and mixed stand. According to the previous study examining the suitable window sizes for deriving texture features for the study area (Chiu and Couloigner, 2004a; 2004b), an arbitrary window of $7 \times 7$ pixels is applied to randomly sampled training classes for the examination of the semivariogram behaviors. The semivariance is a directionally dependent estimator. However, we chose to use the omnidirectional semivariogram in this study.

4 RESULTS AND DISCUSSIONS

4.1 Semivariogram

The semivariograms of the three main classes are derived from the three Tasseled Cap transformation indices in order to verify if the semivariogram textures can capture the landscape structures between the different land cover types. The semivariogram of wetland is clearly different from the other chosen classes: deciduous forest and mixed stand (Figure 3). Because the wetland’s transitional
characteristics are spectrally reflected on the image, this class does not show the same homogeneity than the other two. Especially in the greenness index, the semivariances of wetlands are much higher than the deciduous forests and mixed stands ones. The wetland’s semivariogram curves reach a local peak at a lag distance of 4~5 pixels and then drop down, while the curves for deciduous forest and mixed stand rise steadily upward to a larger lag distance beyond the examining window. These figures also imply that the average size of wetlands distributed in the study area is smaller than the other two classes. The interpretation is coincident with the geography of the study area. These findings are positive to our proposed approach that introduces the semivariogram texture into the fuzzy clustering algorithm.

4.2 Fuzzy clustering algorithms

The default values used for FCM and semivariogram guided FCM (SGFCM) are identical: \( m = 2 \), \( \varepsilon = 10^{-5} \), and \( C = 3 \). The three classes correspond to deciduous forests, wetlands, and mixed stands. Figure 4 shows the distributions of clusters in the feature space for the site A. As FCM does not incorporate information from the spatial domain and uses the Euclidean distance as measure, the three clusters are well separated with almost the same size and a spherical shape. Since the spectral and spatial vagueness are inherited in the transition areas, the ellipsoid distribution gives a more realistic description of the data set than the spherical one does. SGFCM using the Mahalanobis distance in the clustering iteration demonstrates a significantly different cluster distribution in the feature space. Overlapped clusters in the feature space show the ambiguity inherited in the data set that may lead to classification uncertainty. Pixels are classified to the “belonging” classes according to their membership degrees. “Transition classes” are created to allocate ambiguous feature points scattered in the overlaps. Four transition classes are then created in addition to the three main classes. Transition 1-2 represents ambiguous areas of deciduous forest and wetland; Transition 1-4, deciduous forest and mixed stand; Transition 2-4, wetland and mixed stand; and Transition 1-2-4 the vagueness of the three main classes.

![Figure 4. Scatter plots of the feature points from the Tasseled Cap transformed data set. Two different clustering algorithms are applied to the site A: (a) FCM and (b) SGFCM.](image)

4.3 Classifications

To evaluate the effectiveness of the SGFCM classifier for wetland mapping, two sites are examined for accuracy assessment. Figure 5 shows the reference data (in yellow) from the national topography database (NTDB) of Canada and the mapping results of the site A. For visual interpretation, three areas are marked as examples in Figure 5 (b) and (c) to show the differences of the two mapping results. For the area noted 1, a wetland patch is shown in the reference data. However, the FCM classifier can detect only few pixels belonging to that wetland while SGFCM extracts the whole wetland area. For the area noted 2, FCM misclassifies the patch as mixed stands. Although SGFCM
does not correctly classify the patch as wetland, it denotes the patch as a transition of wetlands and mixed stands. For the area noted 3, no wetlands are indicated in the reference data. FCM misclassified most of the deciduous forests boundaries as wetland, whereas SGFCM does not have such errors in mapping. Similar results can be found in Figure 6 when examining the site B.

To quantify the accuracy and the errors, confusion matrices and classification accuracies of the two testing sites are summarized in Table 1 and Table 2. Because only wetland class can be expected from the reference database, classes used in the accuracy assessment include only water, wetland, and non-wetland. Since water bodies are excluded for the clustering iteration, the producer’s accuracy of water class is one hundred percent. For the accuracy assessment of the site A, FCM provides an overall classification accuracy of 71 percent and the producer’s accuracy of wetland mapping is 57 percent. SGFCM, however, improves the overall accuracy to 86 percent and the producer’s accuracy of wetland mapping reaches 69 percent. The effectiveness of SGFCM is also proved through the accuracy assessment of the site B. The overall accuracy increases from 70 to 92 percent when using the SGFCM classifier instead of the FCM classifier. When analysing the commission errors of wetland mapping, SGFCM decreases the commission error of both wetland and non-wetland classes substantially: the wetland commission errors are decreased by 20 and 40 percent for the site A and B, respectively.

Figure 5. Classification maps of site A. (a) Reference data (in yellow) from the National Topographic Database (NTDB), Canada-classification from (b) FCM and (c) SGFCM.
Figure 6. Classification maps of site B. (a) Reference data (in yellow) from the National Topographic Database (NTDB), Canada-classification from (b) FCM and (c) SGFCM.

Table 1. Confusion matrix for wetland mapping of the site A (in pixels) for the:

(a) FCM classifier

<table>
<thead>
<tr>
<th>Class</th>
<th>Water</th>
<th>Wetland</th>
<th>Non-wetland</th>
<th>Deciduous forest</th>
<th>Mixed stands</th>
<th>Producer’s Accuracy (%)</th>
<th>Commission Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>294</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>100</td>
<td>0</td>
</tr>
<tr>
<td>Wetlands</td>
<td>0</td>
<td>2286</td>
<td>574</td>
<td>1137</td>
<td>0</td>
<td>57.0</td>
<td>81.0</td>
</tr>
<tr>
<td>Non-wetland</td>
<td>0</td>
<td>9779</td>
<td>12841</td>
<td>13089</td>
<td>0</td>
<td>72.6</td>
<td>6.2</td>
</tr>
</tbody>
</table>

Overall accuracy = 71.3%

(b) SGFCM classifier

<table>
<thead>
<tr>
<th>Class</th>
<th>Water</th>
<th>Wetland</th>
<th>Non-wetland</th>
<th>Deciduous forest</th>
<th>Mixed stands</th>
<th>Trans. 1-2</th>
<th>Trans. 1-4</th>
<th>Trans. 2-4</th>
<th>Trans. 1-2-4</th>
<th>Producer’s Accuracy (%)</th>
<th>Commission Error (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Water</td>
<td>294</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>100</td>
<td>0</td>
</tr>
<tr>
<td>Wetlands</td>
<td>0</td>
<td>2761</td>
<td>252</td>
<td>70</td>
<td>246</td>
<td>52</td>
<td>616</td>
<td>0</td>
<td>0</td>
<td>69.1</td>
<td>61.0</td>
</tr>
<tr>
<td>Non-wetland</td>
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<td>4237</td>
<td>15354</td>
<td>190</td>
<td>9242</td>
<td>1511</td>
<td>5535</td>
<td>0</td>
<td>0</td>
<td>88.0</td>
<td>3.8</td>
</tr>
</tbody>
</table>

Overall accuracy = 86.2%
A novel fuzzy clustering algorithm has been developed in this study for wetland mapping. The semivariogram guided fuzzy c-means (SGFCM) clustering method modifies the standard FCM by incorporating the image texture information into the clustering iterations. Semivariograms are utilized as representations of the spatial patterns of landscape structures for different land cover types. The concept is different from the traditional image classification incorporating textural images. Most of such studies derive several textural images from given windows and compare the classification accuracy to find out the optimal window size and input feature combinations. However, the optimal window size and the feature combinations may vary because of the different data set. SGFCM is a partial supervision classifier that considers the geospatial variation of the data set and can be generally applied to any data set. When comparing with the FCM classifier, the SGFCM classifier demonstrates its effectiveness by increasing the overall accuracy to 86 and 92 percent and decreasing the commission error by 20 to 40 percent for the testing site A and B respectively. Furthermore, instead of using a maximum operation, a threshold defuzzifier captures the vague area which normally leads to the classification uncertainty. Highlighting the uncertainty areas helps users to know the error source of the accuracy assessment. When applying the SGFCM classifier, a noteworthy procedure is the selection of training sites to derive the semivariogram patterns of classes. Examining the semivariograms from several training sites of a class is important before selecting a representative training semivariogram pattern for guiding the fuzzy classifier.

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