INCORPORATING SPATIAL INFORMATION INTO FUZZY CLUSTERING OF MULTISPECTRAL IMAGES

Jirasak Sittigorn*
Yuttapong Rangsanseri**
Punya Thitimajshima***

*Department of Telecommunications Engineering, Faculty of Engineering
King Mongkut's Institute of Technology Ladkrabang, Bangkok 10520, Thailand
Tel: (66-2) 326-4242, Fax: (66-2) 326-4554,

**Department of Telecommunications Engineering, Faculty of Engineering
King Mongkut's Institute of Technology Ladkrabang, Bangkok 10520, Thailand
Tel: (66-2) 326-4242, Fax: (66-2) 326-4554,
E-mail: rangsanseri@yahoo.com

***Department of Telecommunications Engineering, Faculty of Engineering
King Mongkut's Institute of Technology Ladkrabang, Bangkok 10520, Thailand
Tel: (66-2) 326-4242, Fax: (66-2) 326-4554,

KEY WORDS: Fuzzy c-means, Clustering, Spatial information, Multispectral image

ABSTRACT: Fuzzy c-means clustering algorithm has been successfully applied for unsupervised classification of multispectral images. The conventional method assigns each data point to a cluster by discarding its spatial information. For the real image data, pixels with similar features usually appeared together spatially. However, measurement noise introduced during the imaging process may alter the feature value of a pixel to the extent that it is misclassified. In this paper, we propose an unsupervised classification method for multispectral image based on fuzzy c-means algorithm. The method exploits both the spectral signature and the spatial contextual information of the pixel. The additional spatial information utilized by our algorithm enables it to achieve better segmentation of the image compared to the conventional method.

1. INTRODUCTION

Clustering is a method for dividing scattered groups of data into several groups. It is commonly viewed as an instance of unsupervised learning. The grouping of the patterns is accomplished through clustering by defining and quantifying similarities between the individual data points or patterns. The patterns that are similar to the highest extent are assigned to the same cluster. (Pedrycz, 1997)

Fuzzy *c*-means is a method of clustering, which allows one piece of data belong to two or more clusters. The use of the measurement data is used in order to notice the image data by considering in spectral domain only. However, this method is applied for searching some general regularity in the collocation of patterns focused on finding a certain class of geometrical shapes favored by the particular objective function. That is considered in the spatial domain, which FCM never utilize this property. Spatial information added while cluster data with spectral information has some advantages over the procedure of a spectral segmentation procedure followed by a spatial filter. Furthermore, the usage of a priori spatial information can improve the separation of two overlapping clusters, when two overlapping clusters in the spatial domain correspond to two different objects in the spatial domain.

In this paper, we use spatial information in an unsupervised fuzzy clustering technique by considering information within a 3×3 neighborhood of each pixel. The synthetic image was depicted for showing the better result from our clustering technique before applying with the JERS-1/OPS image.

2. FUZZY C-MEANS CLUSTERING

The Fuzzy c-Means (FCM) algorithm is an iterative partitioning method that produces optimal c-partitions (Bezdek, 1984). The method computes the cluster centers and generates the class membership matrix (Zadeh, 1965). An optimal fuzzy c-partition is one that minimizes the generalized least-squared error function as

$$J_m(U,v) = \sum_{k=1}^{N} \sum_{i=1}^{c} u_{ik}^{m} \| x_k - v_i \|^2 \tag{1}$$

where $X = \{x_1, x_2, x_3, \ldots, x_N\} \in R^P$ is the p-dimensional data k. c is the number of clusters, 2 $c < N$. m is a weighting exponent, 1 $m < \infty$. $U = \{u_{ik}\}$ is the fuzzy c-partition, u_{ik} is membership of x_k in the cluster i. v_i is the centroid of the cluster i. $\|x_k - v_i\|$ is Euclidean distance between the feature vector x_k and the cluster centroid v_i.
The weighting exponent m has the effect of reducing the squared distance error by an amount that depends on the observation's membership in the cluster. As $m \rightarrow 1$, the partitions that minimize J_m become increasingly hard. Conversely, higher values of m tend to soften a samples cluster membership, and the partition becomes increasingly blurred. Generally m must be selected by experimental means.

Fuzzy partition is carried out through an iterative optimization of (1) with the update of the cluster centers v_i and membership u_{ik} as (2) and (3).

$$v_i = \frac{\sum_{k=1}^{N} (u_{ik})^m x_k}{\sum_{k=1}^{N} (u_{ik})^m} \tag{2}$$

$$u_{i,k} = \left[\sum_{j=1}^{c} \left(\frac{d_{ik}}{d_{jk}} \right)^{2/(m-1)} \right]^{-1} \tag{3}$$

where $d_{ik} = \|x_k - v_i\|$ is Euclidean distance between the feature vector x_k and cluster centroid v_i. The criteria in this iteration will stop when $\max\left\{\left| u_{ki}^{(t)} - u_{ki}^{(t-1)} \right|\right\} < \boldsymbol{e}$, where $\boldsymbol{e}$ is an allowed tolerance value.

3. THE PROPOSED METHOD

Our clustering technique exploits the spatial information within a 3 × 3 window of the image pixel. If the 3 × 3 patch belongs to the same class, then the center pixel should be smoothed by its neighboring pixels so that nine pixels in the window have similar membership values in one of the clusters.

For our method, which consider spatial information in fuzzy c-means algorithm. Let $X = \{x_{1,1}, \ldots, x_{i,j}, \ldots, x_{n_1,n_2}\}$ be the set of feature vector associated with an image of size $n_1 \times n_2$, where $x_{i,j} \in R^P$ is p-dimensional feature vector at pixel location (i, j).

For every pixel in the image, we can compute the distance between its feature vector and the feature vector of its neighbors, $\partial_{l_1,l_2}^{r,s}$, at the location (r, s) as follows:

$$\partial_{l_1,l_2}^{r,s} = \left(x_{r,s} - x_{r+l_1,s+l_2} \right)^T \left(x_{r,s} - x_{r+l_1,s+l_2} \right) \tag{4}$$

We can be defined m is a global average of the local average Euclidean distance between the feature vector $x_{r,s}$ and its neighbor $x_{r+l_1,s+l_2}$ in 3 × 3 window of image pixel as:

$$m = \frac{1}{n_1 n_2} \sum_{r=1}^{n_1} \sum_{s=1}^{n_2} \left[\frac{1}{8} \sum_{l_1=-1}^{1} \sum_{l_2=-1}^{1} \partial_{l_1,l_2}^{r,s} \right] \text{ with } (l_1, l_2) \neq (0,0) \tag{5}$$

Let us define a weighting function $l_{l_1,l_2}^{r,s}$, which is the weighting of Euclidean distance between the feature vector $x_{r,s}$ and its neighbor $x_{r+l_1,s+l_2}$ as in (6).

$$l_{l_1,l_2}^{r,s} = \frac{1}{1+e^{-(\partial_{l_1,l_2}^{r,s}-m)/s}} \tag{6}$$

We applied the generalized least-squared error function, cluster centroid and membership by change variable d_{ik} and x_k to $D_{i,r,s}$ and $\hat{x}_{r,s}$, respectively.

$$J_m(U,v) = \sum_{r=1}^{n_1} \sum_{s=1}^{n_2} \sum_{i=1}^{c} u_{i,r,s}^m D_{i,r,s} \tag{7}$$

$$v_i = \frac{\sum_{r=1}^{n_1} \sum_{s=1}^{n_2} u_{i,r,s}^m \hat{x}_{r,s}}{\sum_{r=1}^{n_1} \sum_{s=1}^{n_2} u_{i,r,s}^m} \tag{8}$$

$$u_{i,r,s} = \left[\sum_{j=1}^{c} \left(\frac{D_{i,r,s}}{D_{j,r,s}} \right)^{1/(m-1)} \right]^{-1} \tag{9}$$

where $D_{i,r,s}$ is dissimilarity between the feature vector $x_{r,s}$ and cluster centroid v_i as (10). Dissimilarity index relative influenced of center pixel and neighbor pixels. While $\hat{x}_{r,s}$ is dissimilarity of $x_{r,s}$ as (11).

$$D_{i,r,s} = \frac{1}{8} \sum_{l_1=-1}^{1} \sum_{l_2=-1}^{1} \left[d_{i,r,s}^2 \, l_{l_1,l_2}^{r,s} + d_{i,r+l_1,s+l_2}^2 \left(1 - l_{l_1,l_2}^{r,s}\right) \right] \text{ with } (l_1, l_2) \neq (0,0) \tag{10}$$

where $d_{i,r,s}$ is Euclidean distance between the feature vector $x_{r,s}$ and cluster centroid v_i.

$$\hat{x}_{r,s} = \frac{1}{8} \sum_{l_1=-1}^{1} \sum_{l_2=-1}^{1} \left[l_{l_1,l_2}^{r,s} x_{r,s} + \left(1 - l_{l_1,l_2}^{r,s}\right) x_{r+l_1,s+l_2} \right] \text{ with } (l_1, l_2) \neq (0,0) \tag{11}$$

The first step of our method is to generate an initial random membership matrix (U) and use this random membership matrix as weight of each sample to belong to each cluster, then computes the centroid of each cluster with consider spatial information. The new cluster centers are used to update the membership matrix. The updated membership matrix is compared with the previous ones. If the difference is greater than some threshold, then another iteration is computed, otherwise the algorithm is stopped.

Our method can be described as follows:

1. Set input feature vector from image and define value for c, m, s and e.
2. Initialize the membership matrix U by a random generator size of $c \times (n_1 \times n_2)$ by a random generator.
3. Compute weighting function and $\hat{x}_{r,s}$ using (6) and (11).
4. Repeat
   (a) Compute cluster centroids and dissimilarity using (8) and (10).
   (b) Used dissimilarity for calculate new membership using (9).

   Until $\max\left\{\left|u_{i,r,s}^{(t)} - u_{i,r,s}^{(t-1)}\right|\right\} < e$.
5. Label each pixel with the cluster number corresponding to the highest membership value.

4. EXPERIMENTAL RESULTS

In this experiment, we tested the conventional FCM and our clustering technique with a three-band synthetic image of size 64 $\times$ 64 and a JERS-1/OPS image composing three bands of size 256 $\times$ 256. The following default values are used: $m = 2$, $s = 10$ and $e = 10^{-5}$.

In the first example, a synthetic image was created as different objects in three colors with background of another color, as shown in Figure 1(a). This image was then corrupted by a 15% additive Gaussian noise, in Figure 1(b), as used as input to the clustering algorithms. Figure 1(c) and 1(d) showed the segmented images into four clusters, resulted by the conventional FCM and by our method, respectively. With the conventional FCM, we obtained 27 pixels misclassified, whereas our method reduced the error to only 15 pixels.

The second example is carried out on a JERS-1/OPS image, a color-composite version of the image is showed in Figure 2(a). The clustering was performed both by the conventional FCM and by our method, and the results are shown in Figure 2(b) and 2(c) respectively. The difference in both figures was highlight by circles where we can see that our method yields better result than the conventional FCM because it can reduce the spurious noise and enhance the segmentation regions.

5. CONCLUSION

Our clustering technique uses spatial information to improve the conventional FCM for unsupervised of classification multispectral images. The segmented images show more homogeneous regions when we compare with the conventional FCM, which do not use the spatial information.

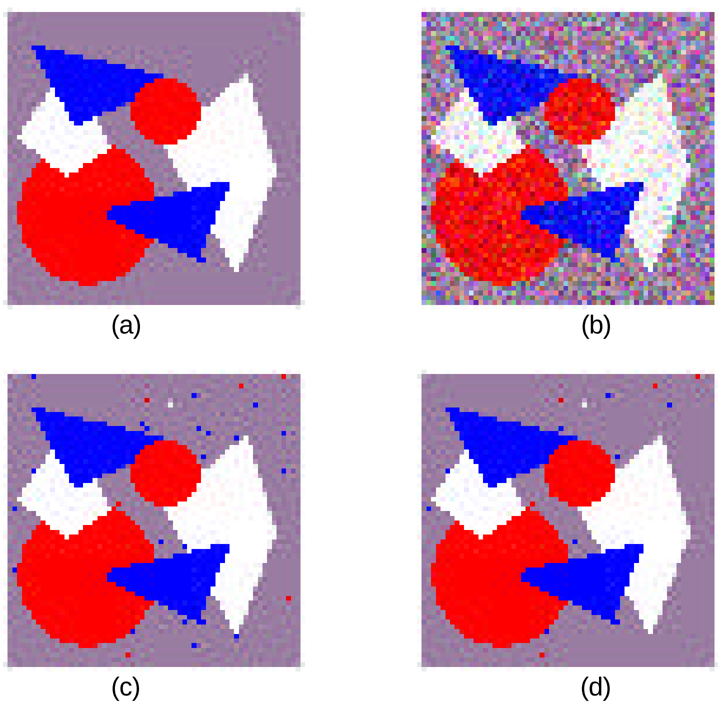
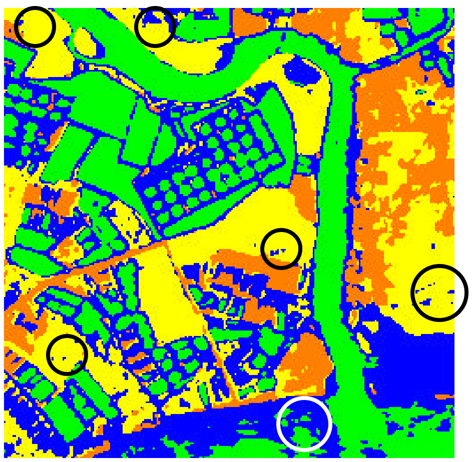
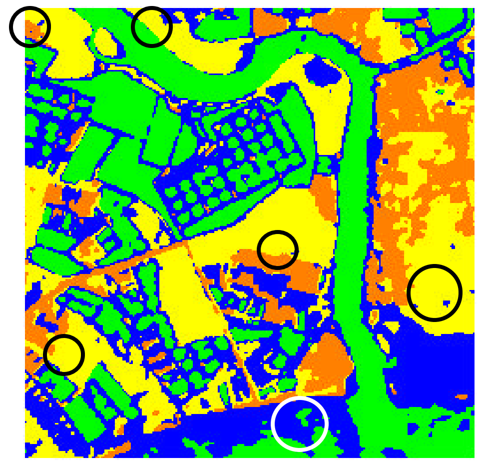


Figure 1: Experiment result on a synthetic image. (a) The original image. (b) The corrupted image by 15% additive Gaussian noise. (c) and (d) Segmented images obtained by the conventional FCM and by our method, respectively.

(a)



(b)



(c)

Figure 2: Experiment result on a JERS-1/OPS image. (a) The original image. (b) and (c) Segmented images obtained by the conventional FCM and by our method, respectively.

6. ACKNOWLEDGEMENT

The authors wish to thank the National Research Council of Thailand (NRCT) for providing the satellite image.

7. REFERENCES

Bezdek, J.C., Ehrlich, R. and Full, W., 1984. FCM: the Fuzzy c-Means clustering algorithm. Computers and Geosciences, 10, pp. 191-203.

Pedrycz, W., 1997. Fuzzy clustering with partial supervision. IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics, 27(5), pp. 787-795.

Zadeh, L.A., 1965. Fuzzy sets. Information and Control. 8(3), pp. 338-353.