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FUZZY C-MEANS CLUSTERING USING SPATIAL INFORMATION WITH APPLICATION TO REMOTE SENSING

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ABSTRACT: Fuzzy *c*-means (FCM) clustering is one of well-known unsupervised clustering techniques, which can be used for unsupervised image segmentation. The measurement data considered from an unsupervised fuzzy clustering technique is only used to reveal the underlying structure of the data and segment the image in regions with similar spectral properties. So this method has not relationship between pixels in the spatial domain, but it just depends on the spectral domain. In this paper, we add a priori spatial information with the FCM clustering for improving the segmentation result. Each pixel condition based on the membership values of neighboring pixels in the spatial domain are updated while iterates the FCM step. As a result, this method swaps between the spectral domain and the spatial domain during the clustering process. The method was tested with color images as well as satellite multispectral images. The results showed that this modified version is better than the standard FCM.

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 then 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) Clustering analysis is based on partitioning a collection of data points into a number of subgroups, where the objects inside a cluster (a subgroup) show a certain degree of closeness or similarity.

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 the modification of an unsupervised fuzzy clustering technique to guide the clustering process by adding a-priori geometrical information in order to improve the final segmentation result. A priori geometrical information used in this experiment is only the local spatial neighbourhood. The pepper image was depicted for showing the better result before applying with the JERS-1/OPS image used in this research.

2. FUZZY *C*-MEANS CLUSTERING

The fuzzy *c*-means method (Bezdek, 1981) is frequently used in pattern recognition. It is based on minimization of the following objective function, with respect to U, a fuzzy *c*-partition of the data set, and to V, a set of K prototypes:

$$J_m(U,V) = \sum_{j=1}^{n}\sum_{i=1}^{c} u_{ij}^m \left\| X_j - V_i \right\|^2, \quad 1 \le m < \infty \tag{1}$$

where m is any real number greater than 1, u_{ij} is the degree of membership of X_j in the cluster i, X_j is the jth of d-dimensional measured data, V_i is the d-dimension center of the cluster, and ||*|| is any norm expressed the similarity between any measured data and the center.

Fuzzy partition is carried out through an iterative optimization of (1) with the update of membership u_{ij} and the cluster centers V_i by:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{d_{ij}}{d_{ik}}\right)^{\frac{2}{m-1}}} \tag{2}$$

$$V_i = \frac{\sum_{j=1}^{n} u_{ij}^m X_j}{\sum_{j=1}^{n} u_{ij}^m} \tag{3}$$

The criteria in this iteration will stop when $\max_{ij}\left[\left|u_{ij} - \hat{u}_{ij}\right|\right] < \varepsilon$, where ε is a termination criterion between 0 and 1.

3. GEOMETRICAL GUIDED FCM (GG-FCM) IN PARTIAL SUPERVISION CLUSTERING

The clustering process under partial supervision is to take advantage of an available classification information (Pedrycz, 1997) by using some labeled patterns. The discrimination between labeled and unlabeled patterns is introduced by a two-valued (Boolean) indicator vector b = [b_j], j = 1, 2, …, N with 0-1 entries

where $$b_j = \begin{cases} 1, & \text{if pattern } X_j \text{ is labelled.} \\ 0, & \text{otherwise.} \end{cases}$$

Similarly, the membership values of the labeled patterns are arranged in a matrix form, F=[f_{ij}], where i = 1, 2, …, c, and j = 1, 2, …, n. The component of supervised learning encapsulated in the form of b and F contributes additively to the modified objective function:

$$J_m(U,V) = \sum_{j=1}^{n}\sum_{i=1}^{c} u_{ij}^m \left\|X_j - V_i\right\|^2 + \alpha \sum_{j=1}^{n}\sum_{i=1}^{c}\left(u_{ij} - f_{ij}b_j\right)^m \left\|X_j - V_i\right\|^2 \tag{4}$$

and the update procedure for the partition matrix U is changed into:

$$\hat{u}_{ij} = \frac{1}{1+\alpha}\left[\frac{1 + \left(1 - b_j \sum_{l=1}^{c} f_{lj}\right)}{\sum_{l=1}^{c}\frac{\left\|X_j - V_i\right\|^2}{\left\|X_j - V_i\right\|^2}}\right] + \alpha f_{ij} b_j \tag{5}$$

where α is a scaling factor to maintain a balance between the supervised and unsupervised data, or is the ratio of unlabeled and labeled data, f_{ij} is the membership of the labeled patterns.

The clustering process is alternated between the standard FCM and the GG-FCM by comparing a pixel of the membership value with all surrounding neighbourhoods. This process is defined for measuring the similarity in the spatial domain. As a result, membership values of spurious pixels in the spatial domain can be influenced indirectly when their neighbourhoods have different membership values. The GG-FCM is processed by partition image into submatrix, which is called a partition image. The mean membership deviation compared to the membership of neighbouring pixels is determined:

$$\Delta m_{rc,i} = \frac{1}{s^2 - 1}\sum_{r',c' \in W}\left|u_{r'c',i} - u_{rc,i}\right| \tag{6}$$

where $\Delta m_{rc,i}$ is the mean membership deviation for the pixel at position (r, c) of partition image i, i is the current cluster, W is a neighbourhood window with odd size s, $u_{r'c',i}$ is the degree of membership of the neighbourhood pixel at position (r',c') in the window W of partition image i, and $u_{rc,i}$ is the degree of membership of the center pixel in the window of partition image i.

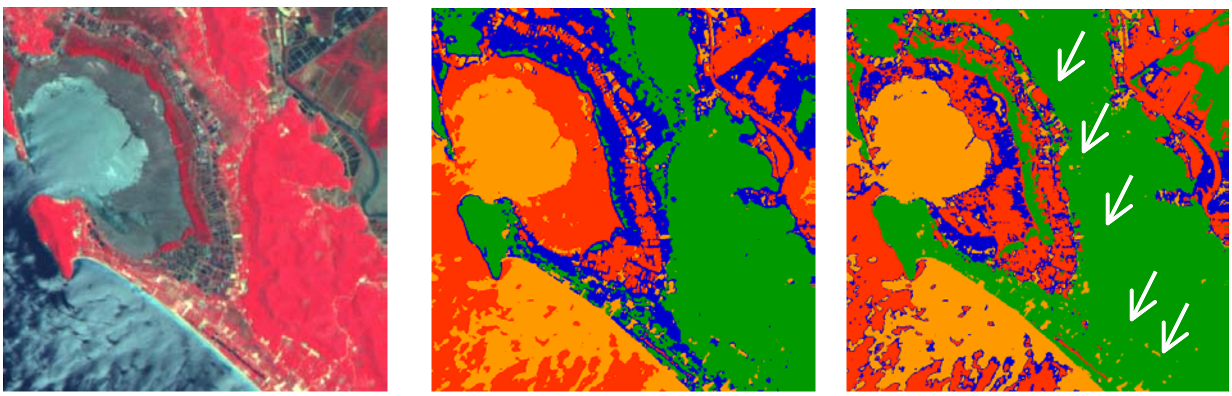
4. EXPERIMENTAL RESULTS

In this experiment, we tested the proposed method with a color image (pepper image) and a JERS-1/OPS image composing three bands of size 256×256. These tested images are shown in Figure 1(a) and 2(a), respectively. The results comparing between the standard FCM and this method are shown in Figure 1(b) and 1(c), and Figure 2(b) and 2(c). Figure 1(a) is defined for 5 clusters, and Figure 2(a) is defined for 4 clusters. The swapping procedure between FCM and GG-FCM is depended on the mean membership deviation (Δm), which is defined by 0.002 in this experiment with 3×3 window size. This discrimination value is given by testing and noticing with the lowest value from the image.

In Figure 1(c), it is shown that the clustering method gives the better result than Figure 1(b) because an extra spatial information result in more homogeneous regions in segmented image. Such regions are shown with white circles in Figure 1(c). Similarly, the better result that can reduce the spurious blobs and enhance the segmentation regions is shown in Figure 2(c), pointed by white arrows, when we tested with the multispectral image JERS-1/OPS.

(a) (b) (c)

Figure 1: Experiment result on pepper image. (a) Input image. (b) and (c) Segmented images as four clusters by the standard FCM and the GG-FCM respectively.



(a) (b) (c)

Figure 2: Experiment result on JERS-1 multispectral image. (a) Input image. (b) and (c) Segmented images as five clusters by the standard FCM and the GG-FCM respectively.

5. CONCLUSION

The GG-FCM can improve the result of the standard FCM for an unsupervise classification. The segmented images show more homogeneous regions when we compare with the standard FCM, which do not use the spatial information. So, we can refer that the spatial information can be enforced and improved the image segmentation process.

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