A Novel Local Similarity C-means Clustering Algorithm for Satellite Imagery Classification

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ABSTRACT

In this paper presents novel local similarity measure c-means clustering for satellite imagery classification.This have been proposed by assimilating the spatial and gray level information of each pixels to provide proper trade-off.This Novel similarity measure can magnify the traditional fuzzy c-means clustering algorithm by producing effectiveness on removing noisy pixels and preserving the original image information.The major offering of this paper is by using weighting factor determining from fuzzy local similarity measure based on spatial attraction model of the pixel.The neighbourhood has weighting factor which balances the noise insensitivity and reducing the unclear artifacts and to maintain the original image details.When compared to other four algorithms this experimental results produces higher reliability and also provides productive clustering algorithm for grouping satellite images.

I. INTRODUCTION

Especially by effort the land information from satellite imagery classification.when the training data are nonexistent ,unsupervised clustering is generally used for satellite sensed imagery.Many clustering algorithms like q-means[2],Expectation Maximum[3], ISODATA[4] , k-Nearest-Neighbour[5],Markov random field[6] ,fuzzy c-means [7],and their changes can be exploited for unsupervised classification. FCM is most commonly used methods. The limited spatial resolution,complexity of ground substance,diversity of disturbance or spectral variation ,Traditional FCM usually produces clustering maps contains salt and pepper noise.

Currently, many researchers have incorporated local spatial information into Traditional FCM objective function to include the spatial constrains. For Example *Pham[*23] proposed a Robust FCM algorithm that lengthened the conventional FCM along with spatial penalty term.*Ahmed et al.*[10],[22] proposed an FCM_S method by propose the spatial neighbourhood term to the FCM objective function.FCM_S is a time consuming process.To decrease the computational problem faced by FCM_S,*Chen and Zhang* [24] developed the two varients,FCM_S1,FCM_S2.It used to simplify the computation of neighbourhood terms.

To increase the speed of the clustering process,enhanced FCM[25] and fast generalized FCM[11]were developed.Still these extended FCM algorithms perform indirectly on the original image,or need a crucial parameter to control the trade off between the robustness to noise and the effectiveness of preserving image details,and the selection of these parameters is difficult[10] to [13].To overcome these problems,*qrinidis and Chatzis* [13] presented a Fuzzy local Information C-Means(FLICM).However this method some difficult in identifying the class boundary pixels and preserving image details[14].To produce more robust results,*Gong et al*[14] proposed a reformulated FLICM with introduces the local coefficient of variation to replace the spatial distance as the local similarity measure.*Li et al* .[16] proposed an FCM with edge and local information based FLICM to reduce edge degradation.

In traditional FLICM algorithm the identification of the center pixels is greatly influenced by its neighboring pixels while the center pixels own feature are not fully considered.It is not a advantage one because the local information encapsulated in the local window.It may produce over-smooth results for important structures and patches.

To address the leading problems,this paper presented a novel local similarity measure c-means clustering for satellite imagery classification.In this paper the local similarity measure is defined to replace the fixed parameter in FCM_S.

The P_{ir} has several advantages and characteristics :

1)P_{ir} uses a pixel spatial attraction model to characterize the relationship between pixels.

2) P_{ir} automatically determined by local spatial and gray level relationship between the center of the pixel and the neighbouring pixels.
3)Using P_{ir} the clustered pixels influenced by its neighbouring pixels and its own features simultaneously.It useful for retaining edges of regions and small patches when removing noise.
4) P_{ir} images the proposed algorithm relatively independent to the noise.
The rest of the paper section -II will deals with FCM clustering algorithm with spatial constrains and its varients,and the FLICM algorithm.section III proposed the A novel local similarity measure c-means clustering for satellite imagery classification.
section IV deals with the performance of the proposed algorithm and its experiments.section V concludes this paper.

II . PRELIMINARY THEORY

Assuming an image $Y=\{y_1,y_2,\ldots\ldots y_l,\ldots\ldots..,y_M\}$,$y_l \in R^m$,is a data set in the m - dimensional vector space , M is the number of feature vectors (number of pixels in the image), and d is the clusters number(2<= d< M).

A. Fuzzy Clustering with Spatial Constraints(FCM_S)

The robustness of the conventional FCM has been introduced Ahmed *et al.* [10] the label of pixel which has been influenced by labels of neighbouring pixels.The objective function of FCM_S is defined as follows :

$$J_m=\sum_{i=1}^{M}\sum_{q=1}^{d}u_{qi}^{p}\|y_i-v_q\|^2+\frac{\alpha}{M_R}\sum_{i=1}^{M}\sum_{q=1}^{d}u_{qi}^{p}\sum_{r\in N_i}\|y_r-v_q\|^2$$

Where y_i is the i^{th} pixel gray value,v_q is the q^{th} cluster prototype, u_{qi} denotes the degree of membership function of y_i belongs to the q^{th} cluster, p is the weighting component,M_R is the cardinality,M_i is the group of neighbourhood pixels in the window throughout i^{th} pixel y_i.The result of the neighbourhood can be controlled by the parameter α. The information about FCM_S will be in [10].

The computation of neighbourhood term of FCM_S is time consuming process.Chen and Zhang [24] has proposed FCM_S1 method to reduce computational load of neighbourhood term in FCM_S. The altered objective function as follows as:

$$J_m=\sum_{i=1}^{M}\sum_{q=1}^{d}u_{qi}^{p}\|y_i-v_q\|^2+\alpha\sum_{i=1}^{M}\sum_{q=1}^{d}u_{qi}^{p}\|\overline{y_i}-v_q\|^2$$

Where $\overline{y_i}$ is the mean of neighbouring pixels around the window y_i .FCM_S1 is not acceptable for impulse noise[24].Then FCM_S2 has been proposed [24] to magnify the robustness of impulse noise.

B. Fuzzy Local Information C-Means Clustering Algorithm

In previous functions of FCM_S,FCM_S1 and FCM_S2 ,the robustness of the noise and the potency of the image details will be maintained by the parameter α.Sometimes these functions may lead to loss in original image details.

To overwhelm these limitations ,FLICM has been introduced to detach noise and to maintain the image details concurrently.

$$G_m=\sum_{j\in Ni_{i\neq j}}\frac{1}{d_{ij}+1}(1-u_{qj})^p\|y_j-v_q\|^2$$

where d_{ij} is the distance between i^{th} pixel and j^{th}pixel .The objective function of the FLICM is as follows:

$$J_m=\sum_{i=1}^{M}\sum_{q=1}^{d}u_{qi}^{p}\|\overline{y_i}-v_q\|^2+G_m$$

The limitations of FLICM which identifies the class boundary pixels and their important structures.

III . LOCAL SIMILARITY MEASURE C-MEANS CLUSTERING

The limitations of the FCM_S , FCM_S1 , FCM_S2 and FLICM has been overcome by Local similarity measure c-means clustering algorithm.In this section III-A provides pixels spatial attraction model definition and section III-B provides local similarity measure and finally section III-C the general framework of this algorithm.

A. Definition of pixel spatial attraction model

The Spatial correlation between each pixel in the image should be effective in the attraction model.The attraction model should include spatial and gray level information.In a cluster 'q' the i^{th} and j^{th} pixel their attraction should be equivalent to their fuzzy memberships

u_{qi} and u_{qj} for each pixels.The square of the spatial distance between the two pixels should be inversely proportional.Therefore ,the pixel spatial attraction $PS_{ij}(q)$ between the two pixels as follows,

$$PS_{ij}(q) = \frac{u_{qi} \times u_{qj}}{L_{ij}^{2}}$$

Where L_{ij} is the spatial distance between i^{th} pixel and j^{th} pixel.

				5				
		5	5	5	5	5		
	5	4	4	3	4	4	5	
	5	4	2	1	2	4	5	
5	5	3	1	y_i	1	3	5	5
	5	4	2	1	2	4	5	
	5	4	4	3	4	4	5	
		5	5	5	5	5		
				5				

Fig:1: represents the structure of neighbourhood local window

B. Novel local Similarity Measure (P_{ir})

The similarity measure focuses the following issues: 1)provides a proper trade-off between the noise insensitivity and the effect of preserving image details; 2)The trade-off has been controlled automatically without any selection of manual parameter ; 3)Based on spatial distances between the center pixel and gray level differences the value has been changed simultaneously.

Based on spatial attraction model,novel similarity measure P_{ir} has been introduced which assimilate the spatial and gray level information.

$$P_{ir} = \begin{cases} PS_{ir}, & i \neq r \\ 0, & i = r \end{cases}$$

Where i^{th} pixel represents center pixel of the local window and r^{th} pixel represents the neighbourhood pixel that contained in M_i . The structure of the neighbourhood of the local window is defined as,

$$M_i = \{r \in M | 0 < (a_i - a_r)^2 + (b_i - b_r)^2 \leq Q\}$$

Where (a_i, b_i) and (a_r , b_r) represents the i^{th} and r^{th} pixel coordinates respectively and Q is the constant which is equal to 2^{L-1} .

C.General Framework of ADFLICM

Thus the ADFLICM is mainly suggested for unsupervised satellite image classification based on P_{ir}. It assimilates both local and gray level information to enhance the smoothness and decrease the edge blurring artifacts.

Therefore the objective function as follows,

$$J_m = \sum_{i=1}^{M} \sum_{q=1}^{D} u_{qi}^{p} \times \left[\left\| y_i - v_q \right\|^2 \frac{1}{M_R} \sum_{\substack{r \in N_i \\ r \neq i}} (1 - P_{ir}) \left\| y_r - v_q \right\|^2 \right]$$

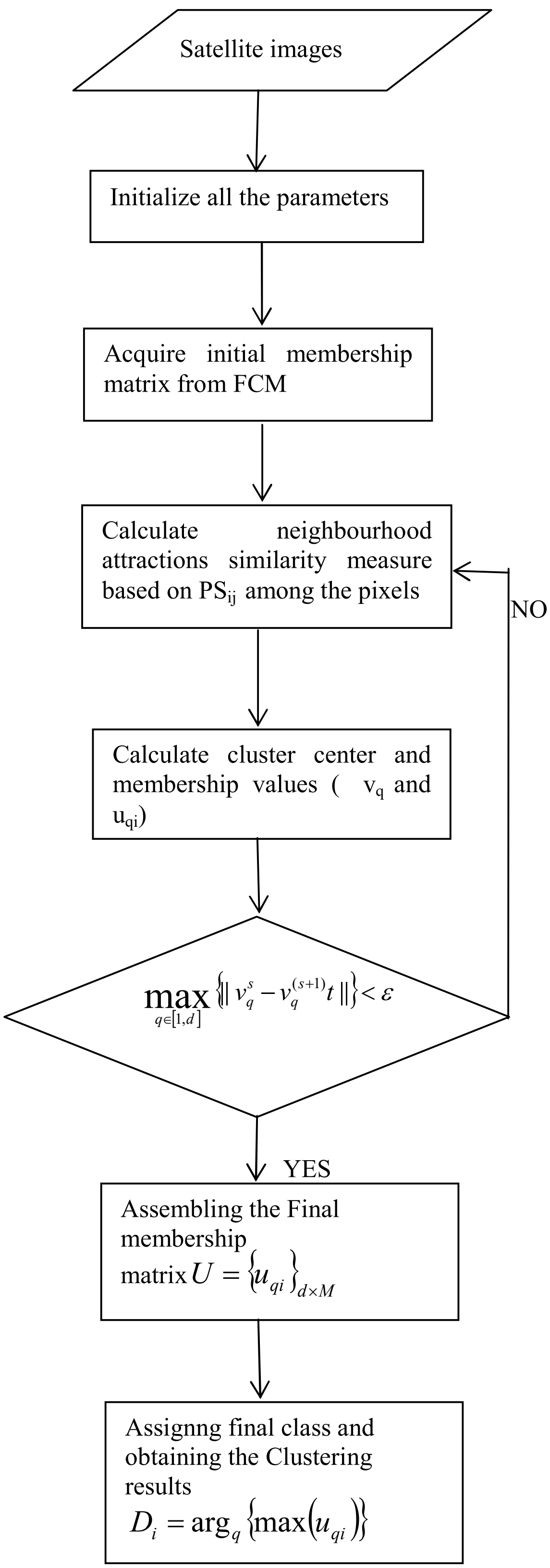
Where M_i will be pointed in section III-B. According to local minimal extreme,the J_m will be calculated based on u_{qi} and v_q are as follows,

$$u_{qi} = \frac{1}{\sum_{j=1}^{d} \left(\frac{\left\| y_i - v_q \right\|^2 + \frac{1}{M_R} \sum_{\substack{r \in M_i \\ r \neq i}} (1 - P_{ir}) * \left\| y_r - v_q \right\|^2}{\left\| y_i - v_j \right\|^2 + \frac{1}{M_R} \sum_{\substack{r \in M_i \\ r \neq i}} (1 - P_{ir}) * \left\| y_r - v_r \right\|^2} \right)^{1/(p-1)}}$$

$$v_q = \frac{\sum_{i=1}^{M} u_{qi}^{p} \left(Y_i + \frac{1}{M_R} \sum_{\substack{r \in M_i \\ r \neq i}} (1 - P_{ir}) * y_r \right)}{\left(1 + \frac{1}{M_R} \sum_{\substack{r \in M_i \\ r \neq i}} (1 - P_{ir}) \right) \sum_{i=1}^{N} u_{qi}^{p}}$$

The flowchart has been proposed for the algorithm.It requires five steps implementation to produce the classification results.

The proposed flowchart as follows,



*Step1(Initialization):*Initialize all the parameters such as cluster number d, weighting component p,the termination criteria ε,and the iteration counter s=0.The FCM algorithm has been implemented to acquire the final fuzzy memberships matrix $U = \{u_{qi}\}_{d\times M}$ will be the initial membership matrix for the this algorithm.

*Step2(Similarity measure P_{ir} calculation):*Based on $PS_{ij}(q)$,the novel similarity measure (P_{ir}) will be calculated.

Step3(center of clusters and membership values calculation): From step2,by using P_{ir} the cluster centers will be calculated by v_q and the membership values will be calculated by u_{qi} .

*Step4(Termination):*When the termination criteria $\max_{q\in[1,d]}\{\| v_q^s - v_q^{(s+1)}t \|\} < \varepsilon$ is encounter,then the iteration will be stop;if else repeat from step2.

Step5(assigning final class to each pixel):After the algorithm coincides ,the final fuzzy membership matrix $U = \{u_{qi}\}_{d\times M}$ will be assembled.Finally greatest membership values will assigned to each pixel i to the class d .

$$D_i = \arg_q\{\max(u_{qi})\}, q = 1,2,3,\ldots\ldots, d$$

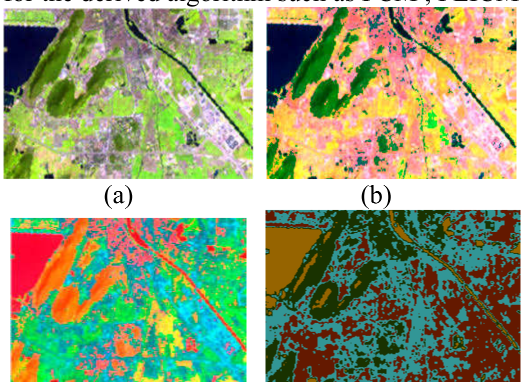
IV.EXPERIMENTAL STUDY AND ANALYIS

In this section , the implementation of the ADFLICM was analysed has been compared with other fuzzy algorithms such as FCM, FLICM .Each algorithm was conducted with trials and the average classification of accuracy and the classifcation results .The ADFLICM algorithm has implemented with Accuracy ,Kappa coefficient ,error rate and true positive and true negative has been used to evaluate the classification performance.

Experiment 1 : TM Image of Xuzhou

In this experiment ,ADFLICM has been examined by using multispectral Landsat Thematic mapper (TM) image and this studied area has been located in China,Xuzhou city. This image has been used for classification of the image.The area of this image will have bare soil, water ,forest land,farm land respectively. The testing samples has been obtained by using reference of TM image.The parameters set in the algorithms d=4, p=2, ε=1e-5, L=2 and $M_{R=}8$

Fig: 2 illustrates the classification results for the derived algorithm such as FCM , FLICM



(a) (b)

(c) (d)

Water

Forest land

Farm land

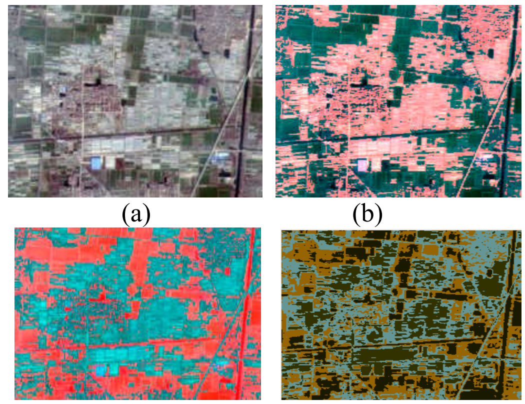
Building and bare soil

Fig 2:Classification results of experiment 1 (a)represents the TM image of Xuzhou (b) classification results produced by FCM (c) classification results produced by FLICM (d)classification results produced by ADFLICM

and ADFLICM respectively.From that FCM produces the classification results weakest among the other algorithms.By obtaining the local spatial and gray level information of the pixels and incorporating both into the objective function FLICM and ADFLICM produces mostly homogeneous images.These two algorithms will produce more satisfactory results aand it clears mostly an isolated pixels.But in FLICM while isolating the pixels some of the image details will be lost.However ADFLICM has classification of heterogeneous pixels.But compared with FLICM ,it produces more accuarate results and also used to preserve the image details than FLICM.This experiment proves that it has th benefit of produing homogeneous and heterogeneous classification of image.

Experiment 2: ZY-3 image of Xuzhou

This experiment has multispectral ZY-3 image used for validation . This studied ZY-3 image is located on China in Xuzhou city.The classification of image has been usd by multispectral band of ZY-3 image.The testing image will include greenhouse,baresoil , plants and aqua and bulidings.The testing samples were acquired and teh parameter used are d=4, p=2, ε=1e-5, L=2, $M_{R=}8$.



(a) (b)

(c) (d)

Water

Green house

Vegetation

Building and bare soil

Fig 3:Classification results of experiment 2 (a)represents the ZY-3 image of Xuzhou (b) classification results produced by FCM (c) classification results produced by FLICM (d)classification results produced by ADFLICM

Fig:3 shows that classification results obtained from the ZY-3 image by using FCM ,FLICM and ADFLICM respectively.In FCM there are many salt and pepper noise in the image. But any how results of FLICM produces feeble results then ADFLICM.The main cause is that the effect of neighbouring pixels will affect the center pixel of the image.Therefore the center pixel is not examined.But this will be overcome in ADFLICM.That is by introducing P_{ir} ,this factor doesn't affect the center pixel and this will yield the proper trade-off between the center pixel and neighbouring pixels.

V.CONCLUSION

In this paper the proposed algorithm ADFLICM is able to control the disadvantages of the traditional FCM by assimilating the local spatial and gray level informaion.This algorithm is able to detach the noisy pixels and reduce the edge blurring artifacts simulataneously.The main merits of this algorithm is by introducing the similarity measure and this prduce the proper trade off between the neighbouring pixel and center pixel.Compared with other algorithm , ADFLICM produces more precise results by visual and quantitative evaluation.Therefore a novel local similarity measure for cmeans clustering produces constructive unsuervised classifiers for satellite images.

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