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Evaluating the potential of particle swarm optimization in clustering of hyperspectral imagery using fuzzy c-means

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Abstract. The unique capabilities of hyperspectral images in expressing the properties of earth surface guides the researchers towards developingmethods that as much as possible, decrease the need of human interference in processing data. A fundamental step in the processing of the hyperspectralimages is the segmentation of them through a clustering process. One ofclustering methods that is used for these images is FCM.Usually we can use two forms of FCM clustering, based on initial values. In both approachescentres of clusters or fuzzy matrix are considered as the primary values and FCM tries to improve the centresof clusters or fuzzy matrix in a repeated process. FCM is very sensitive to initial values and is very unstable and gets easily trapped into the local optimum.In current investigation, mentioned problem is intensified because theincrease in data dimension raises the possibility of local optima in space solution. To overcomethis problem,two FCM approaches are optimized by particle swarm optimization (PSO) in this investigation. Particle swarm optimization method is a powerful optimization tool that is inspired from bird'sbehaviour which is capable of finding global optimum. In this paper the FCM and particle swarm optimization are combined in order to take advantage of their positive points.Experiments on the AVIRIS image, taken over the northwest Indiana's Indian Pine,represent better results for combinatory methods in comparison with two corresponding FCM methods.

Keywords: Particle Swarm Optimization, Clustering, Fuzzy c-means, Hyperspectral images

1. INTRODUCTION

Clustering is a method of partitioning a set into subsets (clusters) in a way that the elements in each cluster are more similar to each other than to the elements in the other clusters(Höppner et al., 1999). In this study, Fuzzy C-Means(FCM) is chosenamong different clustering methods. The FCM algorithm isan iterative process of optimizing a fuzzy objective function. It is a very popular technique due to its efficacy, simplicity and computational efficiency (Yang et al., 2009). A popular method to minimize the FCM objective function is alternating optimization (AO) through the necessary conditions for extreme of the objective function. AO works well for many low dimensional data sets, since the FCM objective function does not possess any local minima for these data sets(Runkler, 2008). However, cluster analysis is recently facing more and higher dimensional data sets (such as hyperspectralimages) for which, the FCM objective function has many local minima.

Therefore, in hyperspectral images with high dimension, AO is not an appropriate method, since it often gets trapped in existing local minima. Hence, many fuzzy clustering algorithms based on evolutionary algorithms have been introduced. One of these methods is PSO. In the following, two of the newest FCM clustering methods based on PSO is presented. (Yang et al., 2009)have combined PSO and FCM based on initialized cluster centres and (Izakian et al., 2009)have hybridized PSO and FCM on the basis of fuzzy matrix initialization.

In this paper, we focus on two mentioned hybridized clustering methods based on FCM and PSO on hyperspectral images. The goal of this study is finding better hybridized FCM clustering method for hyperspectral images based on PSO.

Also, in recent years, two studies have investigated clustering of hyperspectral and multispectral images based on particle swarm optimization. In (Liu et al., 2008), the fuzzy c-means clustering algorithm optimized by particle swarm algorithm (PSO-FCM) is utilized for the image data for wetland extraction. The result of the experiment shows effective and reasonable accuracy of wetland extraction by means of PSO-FCM algorithm. Also(Paoli et al., 2009)have presented a new methodology for clustering hyperspectral images. This method aims to solve the following threeissues simultaneously: 1) estimation of the class statistical parameters; 2) detection of the best discriminative bands without requiring the a priori setting of their number by the user; and 3) estimation of the number of clusters characterizing the considered image.

In this study, four fuzzy clustering methods are investigated. These methods are FCM based on initialized centroid(FCM-V), FCM based on fuzzy matrix initialization(FCM-U), PSO based on FCM-V (PSFCM-V) and PSO based on FCM-U (PSFCM-U).

This paper is structured as follows: Section 2 gives a short review of the FCMmodel and the AO algorithm. Section 3 briefly describes PSO and fuzzy PSO. In section 4 two hybridized methods are presentedbased on PSO and two corresponding fuzzy approaches. Section 5 presents the experiments. The conclusions from these experiments are finally given in Section 6.

2. THE FCM ALGORITHM

FCM partitions set of n objects $x=\{x_1,x_2,\ldots, x_n\}$ inR^d dimensional space into$k$ fuzzy clusters with $v=\{v_1,v_2,\ldots,v_k\}$ cluster centres or centroids. The fuzzy clustering of objects is described by a fuzzy matrix u with n rows and k columns in which n is the number of data objects and the k is the number of clusters. u_{ij}, the element in the i^{th} row and j^{th} column in u, indicates the degree of association of membership function of the i^{th} object with the j^{th} cluster. The clusters of $u$follow the following rules (Izakian et al., 2009).

$$u_{ij}\epsilon[0,1], \qquad 1 \le j \le k, 1 \le i \le n \tag{1}$$

$$\sum_{j=1}^{k} u_{ij} = 1, \forall i = 1, \ldots, n \tag{2}$$

$$0 < \sum_{j=1}^{k} u_{ij} < n, \forall j = 1, \ldots, C \tag{3}$$

The objective function of FCM is to minimize the equation 4.

$$j = \sum_{j=1}^{k}\sum_{i=1}^{n} u_{ij}^{m} d_{ij}^{2}, m \ge 1 \tag{4}$$

Where

$$d_{ij} = \left\|x_i - v_j\right\| \tag{5}$$

In which, m (m>1) is a scalar termed the weighting exponent and controls the fuzziness of the resulting cluster centresv_j. The$u$, fuzzy matrix, and v_j, centroid of the j^{th}cluster, are obtained using equation 6 and 7 respectively.

$$u_{ij} = \frac{1}{\sum_{p=1}^{k}\left(d_{ij}/d_{ip}\right)^{2/(m-1)}} \tag{6}$$

$$v_j = \frac{\sum_{p=1}^{n}\left(u_{ip}\right)^{m} x_p}{\sum_{p=1}^{n}\left(u_{ip}\right)^{m}} \tag{7}$$

With respect to u and v, a popular method, namely alternately optimization (AO), are used to minimize these objective functions. The AO algorithm is iterative and can be showed as Figure 1 (In this study, it is named FCM-V).

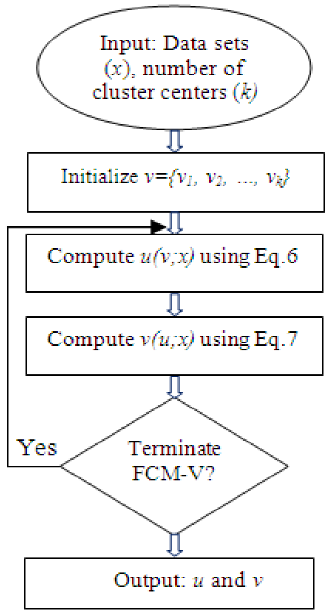


Figure 1: Performance of FCM-V algorithm

If we initialize AO based on *u* instead of *v*, then we lead to dual algorithm AO´. The AO´ algorithm can be showed in Figure 2 and is termed FCM-V in this study.

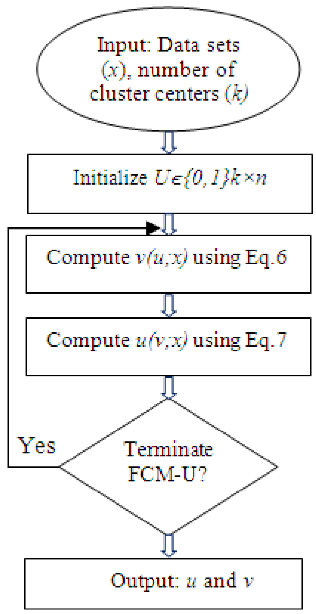


Figure2: Performance of FCM-U algorithm

3. PARTICLE SWARM OPTIMIZATION

PSO is a population based stochastic optimization technique inspired by the social behaviour of bird flock, fish school, etc., and is developed by(Kennedy and Eberhart, 1995). In PSO, each particle is an individual, and the swarm is composed of these particles. The problem's solution space is formulated as a search space. Each position in the search space is a solution of the problem. Particles cooperate to find the best position (best solution) in the search space (solution space). Each particle moves according to its velocity which is computed as:

$$v_i(t+1) = wv_i(t) + c_1 r_1\big(pbest_i(t) - x_i(t)\big) + c_2 r_2\big(gbest(t) - x_i(t)\big) \quad (8)$$

$$x_i(t+1)=x_i(t)+v_i(t+1) \quad (9)$$

In equation 8 and 9,$x_i(t)$ is the position of particle i at time t, $v_i(t)$ is the velocity of particle i at time t,$pbest_i(t)$ is the best position found by particle i itself so far, $gbest(t)$ is the best position found by the whole swarm so far, w is an inertia weight scaling the previous time step velocity, $c_1$and c_2 are two acceleration coefficients that scale the influence of the best personal position of the particle ($pbest_i(t)$) and the best global position ($gbest(t)$), r_1 and r_2 are random variables between 0 and 1.

3.1. Fuzzy PSO

(Pang et al., 2004)proposed a modified PSO for TSP called fuzzy particle swarm optimization (FPSO). In this method, the position and velocity of particles get redefined to represent the fuzzy relation between variables.

In FPSO algorithm the position of particle shows the fuzzy relation from set of data objects, $x=\{x_1,x_2,\ldots,x_n\}$to set of cluster centres, $v=\{v_1,v_2,\ldots,v_k\}$,X, andcan be expressed as follows:

$$X=\begin{bmatrix} u_{11} & \cdots & u_{1k} \\ \vdots & \ddots & \vdots \\ u_{n1} & \cdots & u_{nk} \end{bmatrix} \quad (10)$$

In which u_{ij} is the membership function of the i^{th} object with the j^{th} cluster with constraints stated in equation 1 and 2.

Thevelocity of each particle is a matrix with n rows and k columns.The elements of this matrix are in range [-1, 1]. The equations 11 and 12are respectively used for updating the velocities and positions of the particles based on matrix operations.

$$v_{id}(t+1)=w\otimes v_{id}(t)\oplus(c_1r_1)\otimes(p_{id}(t)-x_{id}(t))\oplus(c_2r_2)\otimes(p_{gd}(t)-x_{id}(t)) \quad (11)$$

$$x_{id}(t+1)=x_{id}(t)\oplus v_{id}(t+1) \quad (12)$$

After updating the position matrix, it may violate the constraints given in equation 1 and 2. So it is necessary to normalize the position matrix. First we make all the negative elements in position matrix to become zero. If all elements in a row of the matrix are zero, they need to be re-evaluated using series of random numbers within the interval [0, 1] and then the matrix undergoes the following transformation without violating the constraints.

$$X_{normal}=\begin{bmatrix} u_{11}\Big/\sum_{j=1}^{k}u_{1j} & \cdots & u_{1k}\Big/\sum_{j=1}^{k}u_{1j} \\ \vdots & \ddots & \vdots \\ u_{n1}\Big/\sum_{j=1}^{k}u_{nj} & \cdots & u_{nk}\Big/\sum_{j=1}^{k}u_{nj} \end{bmatrix} \quad (13)$$

4. TWO HYBRIDIZED CLUSTERING ALGORITHMS

In this section, details of two combinatory methods as well as their algorithms are given.

4.1. PSFCM-V

In this method FCM-V with PSO are integrated to form a hybrid clustering algorithm, which utilizes the merits of FCM and PSO. More specifically, PSFCM-V applies four iterations of FCM after every eight generations of PSO loop such that the fitness value of each particle gets improved(Yang et al., 2009). This algorithm is shown in figure 3.

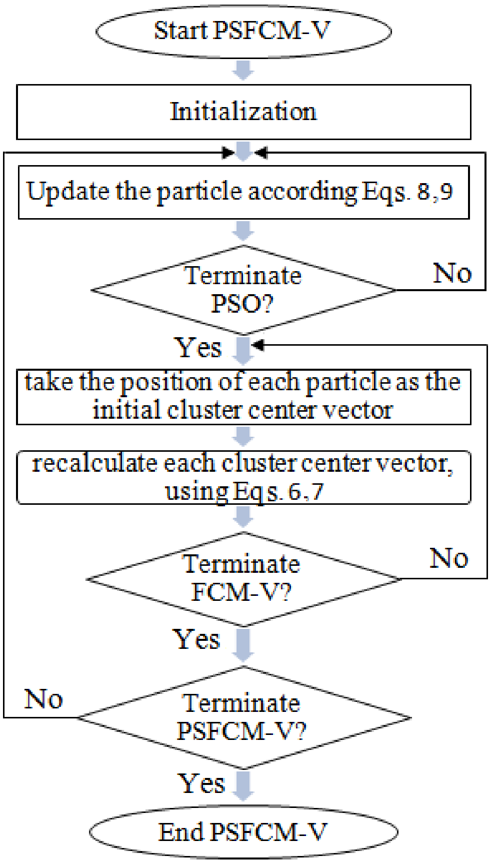


Figure3:PSFCM-V algorithm

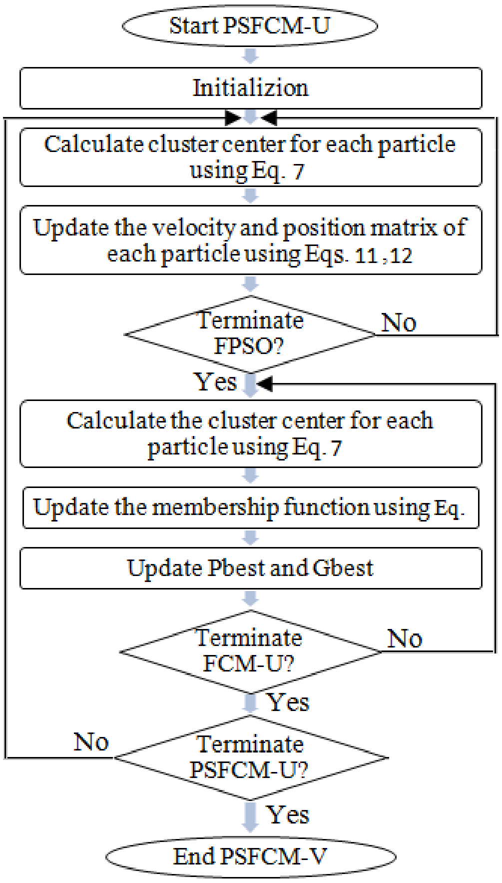


Figure4:PSFCM-U algorithm

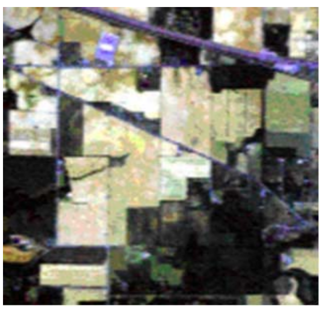
4.2. PSFCM-U

In(Izakian et al., 2009), the FCM-U algorithm is integrated with FPSO algorithm to form a hybrid clustering algorithm called PSFCM-U which utilizes the merits of both FCM and PSO algorithms. PSFCM-U algorithm applies FCM-U to the particles in the swarm every number of iterations (generations) such that the fitness value of each particle is improved. Figure shows PSFCM-U algorithm.

5. results and discussions

5.1. Data Set

The two hybridized methods are evaluated using a sample hyperspectral image which is taken over northwest Indiana's Indian Pine in June 1992 (Figure 4). It was chosen because its ground truth is available for evaluating algorithm. The data consists of 145×145 pixels with 220 bands. The twenty water absorption bands plus fifteen noisy bands were removed from the original image, resulting in a total of 185 bands(Mojaradi et al., 2008).The original ground truth is composed of actually 16 classes, but five classes of them are usedin this study.The ground truth map of five classes is shown in Figure5.These classes are selected because they have suitable spatial distribution.



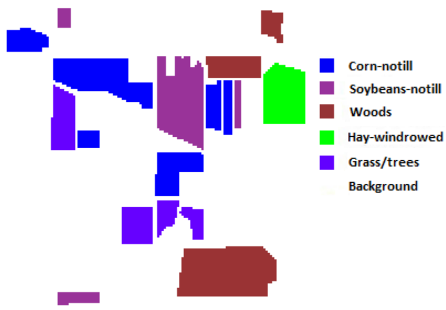


Figure5:Colourcomposite of the image subset

Figure6: Ground truth of the area with five classes

5.2. Performance Measure

In this paper, confusion matrix was used to evaluate the true labels and labels returned by the clustering algorithms as the quality assessment measure(Zhong and Ghosh, 2003). The Kappa coefficient is defined according to equation 14.Also for individual classes, the khat index(Kumar) is calculated using the formula in equation 15.

$$\hat{k} = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} \times x_{+i})} \qquad (14)$$

$$k_i = \frac{Nx_{ii} - x_{i+} \times x_{+i}}{N \times x_{i+} - x_{i+} \times x_{+i}} \qquad (15)$$

In equation 14, $\hat{k}$ is the kappa coefficient and in equation 15k_i is khat index for individual classes, r is the number of columns (and rows) in a confusion matrix, $x_{ii}$is entry $(i, i)$of the confusion matrix, x_{i+} and x_{+i} are the marginal totals of row i and column j, respectively, and N is the total number of observations(Tso and Mather, 2009).

Four methods mentioned i.e. FCM-V, FCM-U, PSFCM-V and PSFCM-U were developed based on the parameters listed in table 1.

Table 1: Parameters used in the clustering of Hyperspectral datasets

Algorithm	parameter	Value
FCM-VandFCM-U	IterCount	100
	M	2
PSFCM-UandPSFCM-V	IterCount	100
	size	13
	w	0.72
	C1	0.49
	C2	0.49

Each algorithm was run 30 times on the AVIRIS data. By comparing the clustering results with the ground truth data, the kappa coefficient for each clustered image was calculated. The best, worst and average obtained results are shown in figure 7.

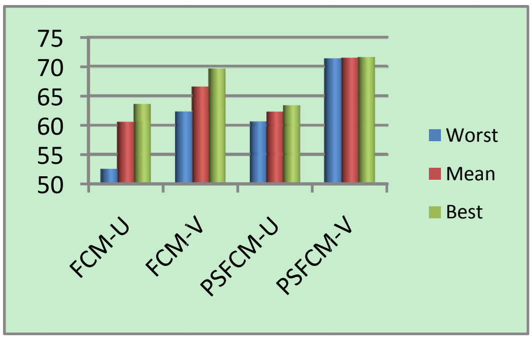


Figure 7: comparison of Kappa coefficient in four clustering methods

According to table 2, FCM-V algorithm outperforms FCM-U for average of kappa coefficient and overall accuracy. The standard deviation of FCM-V and FCM-U methodsshow that they are sensitive to initialized values, which means the stability of these methods, is minimal.

This problem is dissolved in PSFCM-V and PSFCM-Umethods by combining PSO and two fuzzy methods. Standard deviationfor these methods illustrate thattheyare morestablethan the other methods. By comparing the accuracy of presented hybridized methods, it is obvious that PSFCM-U has about 2% better results than FCM-U, and PSFCM-V outperforms FCM-V about 5% in accuracy.

On the other hand, PSFCM-V outperforms PSFCM-Uresulting in 71.49 average kappa coefficients which shows about 9%, better performance result in comparison with 62.28 for the latter method. It's reason is that PSO algorithm with its continuous nature, can better change and move cluster centres in domain search than partitioning matrix with values between 0, 1; also PSFCM-V outperforms PSFCM-U because of better performance of FCM-V than FCM-U in hyperspectral clustering.

Results show that presentation of PSO to FCM-U and FCM-Vslightlypromotesglobal search, but highly increases the stability, in comparison with FCM-U and FCM-V.

Table 2:Min, average and best of kappa coefficient and class accuracies obtained by the four investigated method

	Corn-no till	Grass/trees	Hay-windrowed	Soybeans-no till	woods	Kappa mean | best | std	Overall accuracy mean | best | std
FCM-U	0.4524	0.7517	0.9952	0.5658	0.6701	0.6056|0.6355|0.0418	0.6894|0.7111|0.0284
FCM-V	0.5071	0.7189	0.8972	0.4783	0.9858	0.6651|0.6965|0.0287	0.7414|0.7644|0.0213
PSFCM-U	0.4500	0.7419	0.9952	0.5743	0.6657	0.6228|0.6336|0.0100	0.7006|0.7094|0.0130
PSFCM-V	0.4907	0.7601	0.9930	0.5399	0.9595	0.7149|0.7160|0.0011	0.7776|0.7784|0.0010

6. CONCLUSION

This paper investigates two hybridized clustering algorithms, namely PSFCM-U and PSFCM-V. PSFCM-U and PSFCM-V employ the PSO algorithm to find the set of cluster centres or fuzzy matrixthat minimize a given clustering metric (metric of FCM)respectively. One of the advantages of these methods is that PSFCM-V and PSFCM-Udon't get trapped into local optimum and are more stable than FCM-V and FCM-U. This is due to the ability of the PSO algorithm to perform local and global searchsimultaneously.Experimental results for hyperspectral data demonstrate that these hybridized methods result in better performance than those of the two corresponding FCM methods.

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