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Mixed Pixel Clustering and Classification Techniques: A Review

[1]Er. Sumit Kaur, [2]Dr. R.K. Bansal

[1]Department of Computer Science and Engineering,Guru Kashi University, Talwandi Saboo, India
sumit.bhangu87@gmail.com
[2]Dean Research of Guru Kashi University, talwandi Saboo, India
bansalrajk2009@gmail.com

Abstract--Remote sensor records the reflection factor of the pixels which leads to the confusion of the classification of pixels that are showing the more than one class. These pixels are known as mixed pixels. For example, in a multispectral image from a satellite, a pixel that response to the signal vegetation, water, urban, rocky or forest at same time is a mixed pixel. Classifying mixed pixels to their appropriate class has been the major issue in remote sensing image processing. In this paper, we give a comprehensive review of the techniques used for labeling mixed pixels. First we compare the various clustering techniques used for clustering the image pixels. Then we give the review of the techniques used for classifying the mixed pixels and compare them in terms of their advantages and disadvantages along with the future scope in this area**.**

Keywords: *Mixed pixel, fuzzy, fuzzy C-mean, fuzzy K-mean, PSO, BBO, ACO, Linear discriminate analysis*

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I. Introduction

Presently Digital image processing is the commonly used method for processing the data from remote sensors. Remote sensed data may be processed to get the regional information

A regional map shows the spatial distribution of identifiable Earth surface features and provides an informational description over a given area, rather than a data description (Robert A, 1997). Image classification is used to generate this regional map from the remote sensed image. Image classification converts the spatial data (features) into limited number of classes which show the type of that feature in the sensed image. The main objective of image classification is to identify and depict the features in that image and the type of region these feature actually belongs [9].

For image classification multispectral data is used. Multispectral image is the combination of images acquired from different wavelength for same target area to explore the main features of that image. And for each pixel spectral patterns are used.

These spectral patterns are referred ad digital numbers (DN) basically in numeric values [0-255] [12].

There are number of factors that create the confusion spectral features like, shadowing, atmospheric variability, sensor calibration changes, topography and class mixing.
Problem arise while classifying a multispectral remote sensed image when a pixel response to more than one pure features of classes in that image. Pixels that response to more than one classes are known as mixed pixels. For example, urban and rocky body both classes have different spectral features, if a pixel response to both classes' spectral features that pixel is mixed pixel and does not classified to a particular class. Resolve mixed pixel or labeling them with a particular class is clumsy.

There are two types of pixels present in an image:

a) Pure pixel: Pure Pixels are the pixels which represent a single class. Pure pixels represent areas covered by a single component type. The first step to identify and resolving mixed pixels is to find pure pixels of that image. Pure class pixels are the key input to the various approaches used to resolving or un-mixing problem.

b) Mixed Pixel: mixed pixels are the pixels which are not occupied by a homogeneous class. These pixels represent more than one class. Mixed pixels are created in digital images. Mixed pixels occur at the boundary of the areas, or along long linear features, such as sea and rocky area, where contrasting brightness are immediately adjacent to one another.

Basic reasons of mixed pixels are:

a) Mixed caused by the presence of small, sub pixel targets within the area it represents
b) Mixing as a result of the pixel straddling the boundary of discrete thematic classes
c) Mixing due to gradual transition observed between continuous thematic classes**.**

II. Clustering Techniques

Clustering in image processing is an approach to partitioning the pixels of image into subgroups. These subgroups are known as clusters. The pixels within each subgroup should show a large level of similarity while with the other clusters similarity factor is minimized. Clustering techniques have been used in wide range of problem areas, like data mining, image segmentation, image classifications, etc.

Clustering techniques has divided into two types; supervised and unsupervised. In supervised clustering techniques there is someone externally direct the pixel to which target class it belongs to. In unsupervised clustering there is no external direction, pixels are partitioned and grouped depending upon the distance from one another. In this paper we are focusing on unsupervised clustering techniques using PSO (Particle Swarm Optimization). PSO algorithm is a heuristic evolutionary population based stochastic algorithm that is used to get the optimal (or near optimal) solution to mathematical and qualitative problem [13, 15, 17]. PSO is basically a search engine that has many good features that support to solve global optimization and engineering problems like, it is easy to understand and implement, it required less computational bookkeeping (few lines of code), less memory requirement as compare with other evolutionary algorithms.[6]

The PSO algorithm is initialized with particles- random solutions. Each particle has a velocity and position in the space that is dynamically changed. These changes are depends on the historical behavior of the particle itself and other particle of the group.
In D-dimensional space total number of particle is m.

The position of particle i is $X_i = [X_{i1}, X_{i2}, \dots \dots \dots, X_{iD}$ and velocity of i is$V_i = [V_{i1}, V_{i2}, \dots \dots, V_{iD}]$. The best position of i is$P_i = P_{i1}, P_{i2}, \dots., P_{iD}$. The position of all particles is $P_g = P_{g1}, P_{g2}, \dots., P_{gD}$.

Velocity of a particle is updated by the following equation:

$$v_{id} = w * vid + C_1 * rand_1(\ ) * (p_{id} - x_{id}) + C_2 * rand_2(\ ) * (p_{gd} - x_{id}) \quad \dots\dots\dots\dots (1)$$

$$x_{id} = x_{id} + v_{id} \quad \dots\dots\dots\dots\dots (2)$$

Where d=1,2,…S, w is the inertia weight, it is a positive linear function of time changing according to generation iteration, often changing from 0.9 to 0.2. Suitable selection of inertia weight provides a balance between global and local exploration and results in fewer iterations. The acceleration constants, c1and c2 represents the weighting positions. rand1and rand2 are random functions which change between 0 and 1

Fuzzy clustering is a soft clustering technique in which a pixel is associated with a membership function and can belongs to more than one cluster. The membership function represents the strength of the relationship between that pixel and the cluster. Fuzzy clustering is based on fuzzy logic.

A. PSO based fuzzy K-means

K-means is the one of the simplest partitioning method used for clustering. In this method randomly selected k objects represent initial clusters. Each object is send to the one of the cluster based on distance between the object and the center of the cluster. Center of the cluster is computed as the mean of the cluster. After a new object comes to the cluster center (mean) will be calculated again. Distance between object and center of cluster is calculated by using Euclidean distance. Basically K-means algorithm's objective is to minimize sum of squared error (SSE). It is defined as:

$$\boldsymbol{E = \sum_{i=1}^{k} \sum_{p \in C_i} |p - m_i|^2} \quad \dots\dots\dots\dots\textbf{(3)}$$

E is sum of squared error of the objects of k clusters
k is total number of clusters
p is the object belongs to cluster C_i
m_i is mean of cluster C_i

K-means algorithm has few disadvantages like, local optimization convergence and sensitivity to initial values. To overcome this K-means is integrated with PSO. This algorithm has integrated PSO's global search ability and k-means local search ability.

B. *PSO based Fuzzy c-means*

Fuzzy C Mean(FCM) introduced by Bezdak is the most commonly used clustering algorithm. This method is basically used for pattern reorganization. The degree of fuzziness of a cluster is determined by a fuzzification parameter (m) in range of [l,n]. FCM allows one pixel of image to belong to two or more clusters. The main objective of FCM is to minimize the following objective function:

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} {\mu_{ij}}^m \left\| x_i - c_j \right\|^2 \quad \dots(4)$$

Where 1<=m<=∞
μ_{ij} is fuzzy membership qualification which indicate the membership of i to the j cluster.
x_i is the ith data point. Cluster center is c_j. By using Euclidean distance from center of cluster to the point the distance matrix is$\left\| x_i - c_j \right\|$.

As the FCM is commonly used but it also have some disadvantages like, high computational time, sensitivity to initial guess and sensitive to noise. PSO is integrated with FCM to overcome its disadvantages. While producing the next generation by using PSO-FCM there is more randomcity ,it has the faster convergence rate and not easy to fall into local minimum. The algorithm of PSO-FCM is as:

Set number of cluster C,
Maximum iterations(I) and particle swarm
Cluster center is C_c
Fitness function is rand
Wight is w

Begin

For each particle randomly initialize the memberships, pbest and gbest.

1. for (i=0;i<popsize;i++)

2. evaluate rand
3. Initialize w, weight factor;
4. while (termination condition is not true)
5. for(i=0;i<popsize;i++)
6. if(f(X[i])>pbesti) pbesti=X[i];
7. Update gbest;
8. Update(Position X[i], Velocity V[i]);
9. Evaluate f(X[i]);
10. Find the distance matrix between new gbest and original matrix
11. Update Membership
12 update Membership
13. endfor
Endwhile endfor

C. PSO based Gustafson's-Kessel

Gustason's- Kessel is an extended version of Fuzzy C-Mean[7] by utilize the adaptive distance norm in order to find the different size and various geometrical shapes clusters and clusters at various degrees of orientations. Gustafson & Kessel for each number to clusters calculate Fuzzy covariance matrix and use it as distance norm.

Suppose that clustered data points are n, mj is the total number of clusters that is known, 2<=c<n. Uij denotes the memberships of mj in ith cluster. U is called partitioning matrix.

Gustafson and Kessel use Mahalanobis[7] distance-

- Initialize randomly the partition matric such that U90)2Mfc repeat for l= 1,2,…… …(5)
- Calculate the center of cluster:

$$v_i^{(l)} = \frac{\sum_{i=1}^{N} (\mu_{ik}{}^{(l-1)})^m x_k}{\sum_{k=1}^{N} (\mu_{ik}{}^{(l-1)})^m} \qquad where \quad 1 \le i \le c$$

(6)

- Calculate the distance

$$D_{ikA}^2 = (x_k - v_i)^T A(x_k - v_i) \qquad where \ 1 \le i \le c, \ \ 1 \le k \le N \qquad \ldots(7)$$

The objective function of Gustafson and Kessel algorithm can be computed as:

$$J(X; U, V, A) = \sum_{i=1}^{c} \sum_{i=1}^{N} (\mu_{ik} D_{ikAk}^2) \qquad \ldots..(8)$$

By using Lagrange multiplier A_i is computed as following:

$$A_i = [\rho_i \det(F)_i]^{1/n} F_i^{-1} \qquad \ldots(9)$$

Where Fi is fuzzy covariance matrix of ith cluster

- Compute the covariance matrix

$$F_i^{(l)} = \frac{\sum_{k=1}^{N} \left(\mu_{ik}^{(l-1)}\right)^m (x_k - v_i^{(l)})^T}{\sum_{k=1}^{N} \left(\mu_{ik}^{(l-1)}\right)^m} \qquad where \quad 1 \le i \le c$$

…(10)

- *Update partition matrix*

$$\mu_{ikA}^{l} = 1 \Big/ \left(\sum_{j=1}^{c} \left(D_{ikA}/D_{jkA}\right)^{2/(m-1)}\right) \qquad \ldots(11)$$

$$where \ 1 \le i \le c \,, \qquad 1 \le k \le N$$

$$Until \ \left\| U^{(l)} - U^{(l-1)} \right\| < \epsilon$$

G-K algorithm's transformation utilizes the volume, and more desirable in cases where ellipsoidal clusters of data set having similar volume. But G-K is not effective in the case where the clusters are not differentiate properly and general ellipsoids of varying sizes and orientations, and this made the objective function "flat".

When time parameter is considered, PSO based Gustafson's Kessel converges within few iterations. Distance considered between two clusters is large in case of Gustafson's kessel, hence it provides well separated clusters

III. Various Methods Used for classification of Mixed pixel Problems

1. Linear discriminate analysis

In remote sensing image processing an image is a pixel vector because of the use of various wavelengths' spectral channels, each pixel of the image acquired by a particular spectral channel. Due to this different pixel can be identified by their spectral characteristics in a single vector or mixed with other pixels in pixel vector to form mixed pixels. To perform data analysis on these subpixels or mixed pixels the generally used approach known as LSMA(Linear Spectral Mixture Analysis) is effective.[21][13].

LSMA models an image pixel vector as a linear mixture of endmembers that are assumed to be present in that image. Instead of class labeling LSMA performed abundance fractions estimations to achieve the classification of mixed pixels contained in pixel vector. There are basically two types of LSMA; constrained and unconstrained. In abundance estimation constrained LSMA provide better Results than unconstrained. But constrained LSMA rely on numerical solutions [20][14] and cannot be used to find analytical solutions, whereas on other side unconstrained LSMA has closed form solutions by using second-order statics-based techniques and arrive at the same match filter, such as least square based LSMA [13], signal-to-noise ratio(SNR) based OSP[19] –[16] and Mahalanobis distance-based Gaussian maximum likelihood estimation(GMILE)[18]. LSMA is generally implemented and preferred unconstrained spectral unmixing.

Some of the different approaches used with LSMA to unmix the mixed pixels are and to find the classification errors are:

- AC-FLSMA Abundance-constrained FLSMA.

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- AFCLS-FLSMA Abundance fully constrained least squares FLSMA.
- FVC-FLSMA Feature-vector-constrained FLSMA.
- FLDA Fisher's linear discriminant analysis.
- FLSMA Fisher's LSMA.
- LCDA Linearly constrained discriminant analysis.
- LCMV Linearly constrained minimum variance.
- LSMA Linear spectral mixture analysis.
- OSP Orthogonal subspace projection.
- LSOSP Least squares orthogonal subspace projection (a posterioriOSP)

2. *Fuzzy Classifier*

Fuzzy classifiers used to resolve the mixed problem by applying the fuzzy set theory which imposed partial membership of a given pixel in more than one class. In remote sensed image the geographical object are not identified completely because they have not properly defined boundaries. There is heterogeneity within the class. Because of this the pixel cannot be assigned to particular class this can be represented by fuzzy membership function. By applying fuzzy set theory's membership function on the image uncertain information can be processed by fuzzy. The popular fuzzy set based approaches are the fuzzy c-means clustering (FCM), the probabilistic c-means clustering (PCM).

3. *Artificial Neural Network models*

Artificial Neural Networks are the popular tool used for remote sensed image classification. ANN effectively works on mixed pixel classification from a remote sensed image. Probability Density Function (pdf) in statistical method of a class in feature space used Gaussian distribution. The main problem with this approach is that the feature of earth is too complex to fit in this distribution. On the other hand ANNs works for both high and low dimensional multispectral data classification.
An Artificial Neural Network (ANN) is a software and hardware model inspired by the biological nervous systems, like the Brain. It is interconnected network of processing elements that works together to solve the problem. ANN is trained with examples of the task that is to learn this way of learning called supervised learning. When a network finds the regularities from its inputs and automatically response to represent the different classes of inputs is called unsupervised learning. There are number of ANN are used for image classification by extracting features of texture and then apply back propagation algorithm.

4. *Evolutionary algorithms*

Evolutionary algorithms are the new methods to classifying mixed pixels of a remote sensed image. Evolution algorithms according to the rules of selection or there "search operators", like Recombination and Mutation maintain a population of structures. In the environment each individual from the population has a fitness value and measured of this fitness value. For heuristics exploration recombination and mutation cark the individuals. EAs has multiple components and operators that particularly define a specific EA. Some of important components are:

1. representation (defining individuals)
2. evaluation function (fitness function)
3. population
4. parent selection mechanism
5. variation operators, recombination and mutation
6. survivor selection mechanism(replacement)

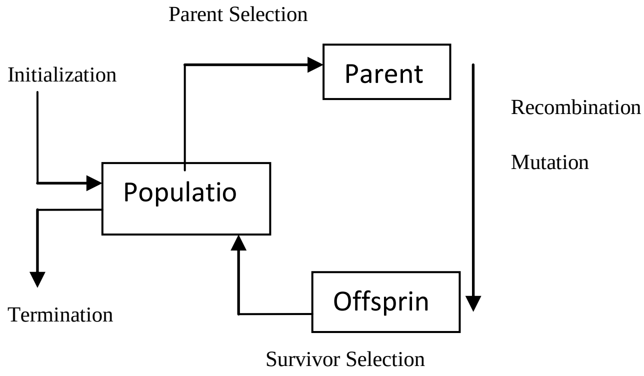

Figure1: Flowchart of general structure of EA

The basic EA algorithm is:

1. Set the initial time t := 0;
2. Initialize the random population of individuals: initpopulation P(t);
3. Evaluate fitness of all initial individuals in population P(t);
4. Test the condition (time, fitness, etc.) for termination : While not done do
5. Increment the time counter: t := 1;
6. For offspring production select sub-population: P' := selectparents P(t);
7. Recombine the "genes" of selected parents: recombine P' (t);
8. Stochastically perturb the mated population: mutate P'(t);
9. Evaluate its new fitness value: evaluate P'(t);
10. From the actual fitness select the survivors: P:= survive P,P'(t);
11. End EA.

There are various Evolutionary algorithms that are used for image classification of remote sensing images.

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Table 1: Compare the two most popular evolutionary algorithms

Methods	Procedure	Pros	Cons
Using BBO	1. Identify pure pixel and mixed pixel dataset. 2. Calculate the HSI value of each habitat(each class) 3. Choose a single mixed pixel and add it to each habitat and then recalculate HSI value of the habitat. 4. The mixed pixel is belongs to the habitat who’s new HSI is greater than other.	1. BBO is easier to implement and there are fewer parameters to adjust. 2. BBO has more effective memory capability then Genetic Algorithms.	This method is not suitable when the number of mixed pixels is large. Because to check each pixel is difficult and time consuming.
Using ACO	1. Identify the dataset for pure pixels and mixed pixels. 2. Generate the clusters of mixed pixel of similar types of pixels(based on intensity values and texture, etc) 3. Set the pheromone variables for both classes to zero (counters). These counter helps to keep the record of pheromone deposited on both path. 4. Apply any classification algorithm like BBO. 5. The path with more pheromone will be chosen at the last. Means when some fixed number of (usually 1/5th) pixels of one cluster are classified then the other are also belongs to the same cluster whose path has more pheromone.	1. This method is suitable when the size of dataset of mixed pixel is larger. 2. By ACO positive feedback accounts for rapid discovery of good solutions. 3. ACO can be used for dynamic applications . 4. It is adapted to new changes like new distance, etc.	Theoretical analysis is difficult as the sequence of random decision is generated, means it is not independent and probability distribution change by iteration

IV. Conclusion and Future scope

This paper presents the review of various techniques of clustering with hybridization of Fuzzy and PSO. From the survey of literature we found that the PSO based Gustafson’s-Kessel, performs better than PSO based fuzzy C-Means and PSO based Fuzzy K-means with extragrades perform better then above said others [4]. There are various classification techniques also used for mixed pixel classification all the other techniques mentioned in this paper are old as compared to evolutionary algorithms, that are modern and easy o implement then others. As from the conclusion of this paper in future we can use PSO base fuzzy technique for clustering and hybridization of ACO and BBO for better and effective results.

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