Hyperspectral Image Segmentation Based on Enhanced Estimation of Centroid with Fast K-Means

Saravana Kumar Veligandan[1] and Naganathan Rengasari[2]
[1]Department of Information Technology, SreeNidhi Institute of Science and Technology, India
[2]Symbiosis Institute of Computer Studies and Research, Symbiosis International (Deemed University), India

Abstract: *In this paper, the segmentation process is observant on hyperspectral satellite images. A novel approach, hyperspectral image segmentation based on enhanced estimation of centroid with unsupervised clusters such as fast k-means, fast k-means (weight), and fast k-means (careful seeding) has been addressed. Besides, a cohesive image segmentation approach based on inter-band clustering and intra-band clustering is processed. Moreover, the inter band clustering is accomplished by above clustering algorithms, while the intra band clustering is effectuated using Particle Swarm Clustering algorithm (PSC) with Enhanced Estimation of Centroid (EEOC). The hyperspectral bands are clustered and a single band which has a paramount variance from each cluster is opting for. This constructs the diminished set of bands. Finally, PSC EEOC carried out the segmentation process on the diminished bands. In addition, we compare the result produce in these methods by statistical analysis based on number of pixel, fitness value, and elapsed time*.

Keywords: *Fast k-means, fast k-mean (weight), fast k- means (careful seeding), and particle swarm clustering algorithm*.

Received March 16, 2015; accepted September 7, 2015

1. Introduction

Hyperspectral imaging is observant with the measurement, analysis, and exegesis of spectra acquired from a given scene at a short, medium or long distance by an airborne or satellite sensor. A hyperspectral image is a high-dimensional image set that specifically consists of 100-300 image channels.

Each channel has a gray scale image that stipulates the spectral response to a specific frequency in the electromagnetic spectrum. These frequencies normally encompass the visible spectrum of light, but most of the channels are focused in the infrared range. This enables a hyperspectral image to reveal features that are not visible in a standard colour image. In an aerial hyperspectral scene an analyst could identify, location of manmade materials or distinguish healthy vs. dead vegetation. For this reason, there is great interest in developing fast detection methods in hyperspectral imaging for applications such as aerial surveillance, mineral and agricultural surveys, chemical analysis, and medical imaging. The advent and growing availability of hyperspectral imagery, which records hundreds of spectral bands, has opened new possibilities in image analysis and classification.

Image segmentation plays an essential role in the exegesis of various kinds of images. Image segmentation techniques can be amassed into diver categories such as edge-based segmentation, region-oriented segmentation, histogram threshold and clustering algorithms. The objective of clustering algorithm is to aggregate data into groups such that the data in each group share homogeneous features while the data clusters are being distinct from each other.

Myriad segmentation techniques have been investigated and plethora conclusions were drawn. Unsupervised techniques based upon the K-Means and Fuzzy C-Means with particle swarm clustering algorithm shows great promise in hyperspectral image segmentation [12, 14].

Hyperspectral scene has carried hundreds of non-overlapping spectral channels of a given scene. Clustering is one method to diminishing the size of these large data sets. Clustering can be defined as supervised, in which the various possible spectra in the scene are known, and unsupervised which has been scrutinizing in this paper. In Fast K-Means (FKM) diminish of hyperspectral process is carried out N-dimensional gray scale image into C classes using a memory efficient implementation of the C-means clustering algorithm. The computational efficiency is attained by using the histogram of the image intensities during the clustering process as a substitute of the raw image data.

In Fast K-Means Weighted Method (FWKM), the cluster has to assess a weight associated with each data in the computation of cluster centers [14, 15]. The procedure of Fast K-Means careful Seeding (FSKM) is choose the first centroid at random from X and each successive centroid from the remaining points according to the categorical distribution with selection probabilities [1] proportional to the point's minimum squared Euclidean distance from the picked out centroid.

The Particle Swarm Optimization (PSO) approach is simple in concept with many advantages. The main advantage of PSO is its robustness in controlling parameter and its high computational efficiency. Obviously, the fitness function is pre-defined and is depend on the problem [6]. Each particle has own coordinate and velocity to change the flying direction in the search space.

Besides, all particles move through the search space by following the current optimum particles. Each particles embraces of a stance vector z, which could represent the candidate solution to the problem, a velocity vector v, and a memory vector p_{id}, which is the better candidate solution encountered by a particle.

The remaining part of the paper is organized as follows: section 2 speculates a brief description of the works related. Section 3 postulates the existing methods whereas section 4 presumes the description of the proposed method. Moreover, Experimental results are portrayed in section 5; and section 6 concludes this paper.

2. Related Work

Veligandan *et al.* [12], segmentations were carried out using Enhanced Estimation of Centroid in hyperspectral scene with K-Means and Fuzzy C-Means. Veligandan and Rengasari [14], the above approach is applied in Pavia University scene include the Fast K-Mean (weighted) method. In [7], a pioneering view on recent advances in techniques for hyperspectral image processing has demonstrated. In [13], a survey of hyperspectral image segmentation techniques for multiband reduction is illustrated. In [9], illustrate a different strategy and exploit the low-dimensional structure, in which the morphological profiles lie, and its suitability to perform sparse classification using spatial and spectral information. In [15], exemplify a novel approach entitled as segmentation of hyperspectral image using J measure based SEGmentation (JSEG) based on unsupervised clustering methods. In [4], it was instigating a new supervised segmentation algorithm for remotely sensed hyperspectral image data which integrated the spectral and spatial information. In [2], it has illustrated a novel technique for unsupervised change detection in multi-temporal satellite images using Principal Component Analysis (PCA) and K-Mean clustering. In [3], it has demonstrated the spectral information is characterized both locally and globally which represents an innovation for probabilistic classification of hyperspctral data. In [7], the examination of different parallel strategized for hyperspectral image analysis on high accomplishment computers; with the purpose of evaluating the possibility of procuring results in valid response times were illustrated. In [11] change detection technique has developed by conducting K-Means clustering on feature vectors. In [10], it has proposed a method that combines the results of a pixel wise support vector machine classification and segmentation map obtained by partitional clustering using majority voting. In [1], it had pioneering explanation about the advantages of fast k-means with careful seeding. In [8], a major barricade for many computationally expensive clustering techniques was solved. In [6], it has narrated with segmentation based on particle swarm optimization. In [5], demonstrate the new supervised Bayesian approach with active learning. In [16], exemplify a texture segmentation algorithm which uses a new descriptor, spectral histogram and skeleton extracting.

3. Existing Methods

3.1. Fast K-Means (FKM)

The method of partition the vectors X into K clusters by applying the well-known batch K-means algorithm.

Rows of X correspond to points, columns corresponds to variable. The output matrix C contains the cluster centroids. The K-element output column vector D contains the residual cluster distortions as measured by total squared distance of cluster member from the centroid.

Algorithm 1: FKM

Read S_n*, c, per,* J_k*,* J_s
//Output: S_n *with clusters //*
  $S_n = S_n$ *% per*
  $X_c = rand(S_n)$
   While $(J_f \le M_{fa})$
    For $i = 1$ *to* n_s
     //Calculate the modified distance
      $D(x_k, x_c) = [(x_k - x_{ci})^T (x_k - x_{ci})]$
       $m = min(D)$
      //Assign the cluster number to point X_i
       X_i *= cluster number*
     next i
    Calculate J_k
   loop
// Calculate the average of the calculated cluster to find new centers X_c *//*
     $X = average(X_c)$
     //Use the whole dataset S_n
     While $(Js \le Ms_1)$
      For $i = 1$ *to* n
       //Compute the modified distance
       $D(x_k, x_c) = [(x_k - x_{ci})^T (x_k - x_{ci})]$
        $D = min(D)$
        $m = min(D)$
       // Assign the cluster number to point X_i
      next i
     Calculate Js
      loop
Stop

3.2. Fast K-Means-Weight (FWKM)

In FWKM, the cluster has to assume a weight associated with each data in the computation of cluster centers. In K-Means algorithm, each data point has an indistinguishable importance in pinpointing the centroid of the cluster. This attribute is not maneuvered out in case of density-biased sample clustering for which every data point portray varied density in the indigenous data. Consequently, the clustering algorithm has to assume a weight analogous with each data in the computation of cluster centers.

Algorithm 2: FWKM

// Input: A set of n data points and cardinal number of clusters (K)

// Output: Centroids of the k clusters
// 1) Initialize the K cluster centers
Read x_i, K_i
for i = 1 to n
K[i] =0
next i
Repeat

//Assign each data point to its nearest cluster center according to the membership function//

$$m\,(c_j \mid x_i) = \frac{\| x_i - c_j \|^{-p-2}}{\sum_{j=1}^{k} \| x_i - c_j \|^{-p-2}} \tag{1}$$

//For each center cj, recomputed the cluster center cj using current cluster memberships and weights //

$$C_j = \frac{\sum_{i=1}^{n} m(x_i / x_j) w(x_j) x_i}{\sum_{i=1}^{n} m(x_i / x_i) w(x_i)} \tag{2}$$

// w (xi) is the weighted associated with each data point
// Until there is no reassignment of data points to new cluster centers//
Until (K[i] != X_i)
for i =1 to K_i
Print K[i]
next i
stop
// The membership function in this algorithm resembles that of the K-harmonic means algorithm.//

3.3. Fast K-Means with Careful Seeding (FSKM) Algorithm

The careful seeding procedure picks out the first centroid at random from *X* and each successive centroid from the remaining points according to the categorical distribution with selection probabilities proportional to the point's minimum squared Euclidean distance from the already picked centroid. This tends to spread the points out more evenly, and if the data is made of K well separated clusters, is likely to pick out an initial centroid from each cluster [15].

These leads speed of convergence and reduce the likelihood of getting a bad solution. This algorithm begins with arbitrary set of cluster centers. At any given time, let *D(x)* denote the shortest distance from a data point x to the closet center already chosen.

Algorithm 3: FSKM

a. *Choose an initial center Ci uniformly at random X.*
b. *Choose the next center Ci selecting Ci = x' Є X with probability* $\frac{D(x)^2}{\sum_{x\in X} D(x)^2}$
c. *Repeat step (b) until we have chosen a total of K centers.*
d. *Proceed as with standard K –means algorithm.*

3.4. Particle Swarm Optimization

A particle swarm is a population of particles, in which each particle is a moving object which could move through the search space and could be attracted to the advantageous positions. The PSO algorithm consists of a swarm of particles flying through the search space.

Each particle's position is a potential solution to the problem. Each particle's velocity is modified based on its distance from its personal best position and the global best position. In other words the particles move according to their experience and that of their neighbor which yields to the best fitness value.

Algorithm 4: Gbest PSO

Initialize particle position and velocity
Do
For (each particle)
Calculate fitness value
If xi is better than P_i
Update P_i
Loop
End
Pick best P_i
If best P_i is better than previous P_g
Update P_g
For (each particle)
Calculate v_i and x_i
If v_i or x_i beyond boundary value
Set v_i or x_i as boundary value
End
While (not meet the Conditions)

Particle Swarm Clustering (PSC) could be viewed as special modification of PSO devised specifically for clustering tasks where each particle represents a candidate solution.

The prime structural polarity between the PSO and PSC algorithms are:

1. In PSC, the particles absolutely compose a solution to the data clustering problem.
2. The PSC does not use an explicit cost function to evaluate the caliber of the particles. Alternatively, the Euclidean distance is wielded as a measure to assess the incongruity between a particle and an object, and particles progress around the space in order to represent statistical regularities of the input data.
3. A self-organizing term, which loco motes the particle towards the input object, was appended to

the velocity equation.

4. For each iteration in PSO, all the particles in the swarm are overhauled. In PSC, the particles to be overhauled are defined by input objects (i.e., only the winner –the one neighborhood to the input data - is overhauled according to Equations (3) and (4).

$$\delta f_i\,(m+1) = w\,(t)\,\delta x_i\,(m) \tag{3}$$

$$f_i\,(m+1) = f_i\,(m) + \delta f_i(m+1) \tag{4}$$

Where $w\,(m)$ is the inertia weight.

Generally, the inertia weight is choosing randomly between of 0.4 to 0.9

4. Proposed Method

Satellites are used to ensure the hyperspectral image of the field area. The flow of the proposed method, hyperspectral image segmentation based on Enhanced Estimation of Centroid with Fast –K-Means is depict as Figure 1 works as follows. To begin with, the hyperspectral scene in mat file format is read; the feature could be extracted based on Mean or Median Absolute Deviation (MAD), Standard Deviation (STD), Variance (VAR).

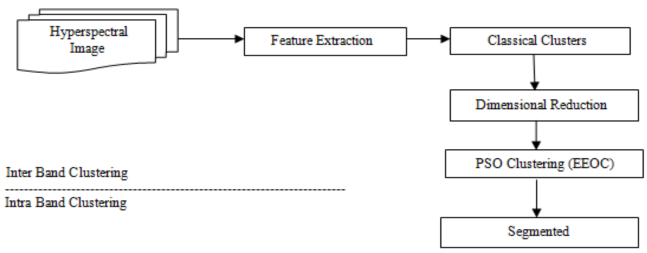


Figure 1. Flow of proposed method.

Moreover apply one of the Fast K-Means clustering methods for clustering process. Besides, (Davies Bouldin index) DB is used to cognize the number of clusters. Furthermore, the dimensional reduction process could be carried out by these clustering methods, by pick out one band from each cluster such as 204 band of the Hyperspectral image are diminished to below twenty bands i.e. one band is pick out according to paramount variance from each cluster.

Segmentation is carried out by Particle swarm clustering. In PSC, we examined the proposed algorithm Enhanced Estimation of Centroid [13, 15]. It is the modification of general PSC by computing the particle that has updated their positions and reinstated the distance matrix only once per iteration.

4.1. Dataset Description

The dataset contains variety of Hyperspectral remote sensing scenes which are ensnared from airborne and satellite. They are Indian Pines, Salinas's scene, Salinas- A scene and Pavia University Scene.

4.1.1. Salinas's Scene:

This scene was collected by the 224 band AVIRIS sensor over Salinas Valley, Southern California. It is characterized by high spatial resolution i.e., 3.7 meter pixels. The area covered comprises 512 linesx217 samples. 20 spectral bands were removed due to water absorption and noise, resulting in a corrected image containing 204 spectral bands over the range of 0.4 to 2.5 µm. It consists of the 16 ground truth classes, along with 7 major classes namely Broccoli-green weeds-2, Stubble, Celery, Grapes-untrained, Soil-vineyard-develop, Corn-senesced-green-weeds, and Vineyard-untrained.

4.1.2. Salinas's _A scene:

A small sub scene of Salinas image is named as Salinas-A. It comprises 86x83 with 204 bands within the same scene which include six classes. They are Broccoli-green weeds-1, Corn-senesced-green-weeds, Lettuce-romaine-4wk, Lettuce-romaine-5wk, Lettuce-romaine-6wk, Lettuce-romaine-7.

4.1.3. Pavia University Scene:

This scene was acquired in 2001 by the ROSIS sensors, with spectral coverage ranging from 0.43 to 0.86 µm. The data is automatically corrected and has spatial resolution of 1.3-m/pixels with 115 spectral bands. The image scene, with size of 610x340, is centered at the University of Pavia, Italy. After removing 12 bands due to noise and water absorption, it comprises 103 spectral channels. It has nine ground truth classes of interest; Water, Trees, Meadow, Parking lot, Bare Soil, Asphalt, Bitumen, Tiles and Shadow.

4.1.4. Indian Pines

This scene was acquired by AVIRIS sensor over the Indian Pines test site in North-western Indiana and consists of 145 times 145 pixels and 220 spectral reflectance bands in the wavelength range 0.4-2.5 x10^{-6} meters. The 20 noisy bands covering the region of water absorption are removed and worked with 200 spectral bands. The Indian Pines scene contains two-third husbandry, and one third natural perennial vegetation.

Algorithm 5: The Algorithm for Proposed Method

- *Step 1: Read the Hyperspectral Scene.*
- *Step 2: Construct the feature matrix based on Mean, Standard deviation and Variances.*
- *Step 3:*
  - *a) Determine the number of Cluster based on David Bouldin Index Step3.*
  - *b) Apply one of the Fast K-Means Clusters Algorithms.*
- *Step 4: Pick out one cluster has maximum variance.*
- *Step 5: Reduced set of band (Below 20 bands).*
- *Step 6: Apply Particle Swarm Clustering (EEOC) for Segmentation.*

- *Step 7: Display the Segmented image.*
- *Step 8: Stop.*

4.2. Enhanced Estimation of Centroid (EEOC)

The restoring rule of EEOC [13] could be summarized as follow. The particle velocity is bounded by Max_v. $fi\ (t)$ denotes the position and the best position of a particle i in relation to the input pattern j. $cj\ (t)$ represents the position of a particle that has been proximate to the input pattern. Each particle position is restored only once in every iteration. This arrives after all possible data points which are proximate to the particle have been individually consider by the particle. This means position update eventuate occurs only i items per iteration, where i is the number of particles in the set.

The Distance Matrix (DM) is reinstated only once per iteration. The overall rock bottom computation is defined to store the best position combination. $fi(m)$ and $ai\ (m)$ denotes position and best position of a particle i in relation to the input pattern. $Ci\ (m)$ represents the position of a particle that has been closest to the input pattered j. $S\ (m)$ represents the best position combination that has achieved overall minimum according to a given fitness function $ft(m)$.

δx is defined by using the above Equations (3) and (4).

Algorithm 6: EEOC:

Algorithm 6 EEoC (data_matrix, iter_func$_{max}$, max$_v$, p$_c$, ϕ)
// Initialize the number of particles as p_c
$p_c = 0$
// calculate the distances of each particles position ‘a’ and the input pattern of the particles position as c
// Update the distance and velocity until $t <$ iter_func$_{max}$
// Find the closest particle (i, j)
$DM = e\ (g_i, f_i) : \Pi\ i, j$ /* *Distance Matrix*
$J = \min (e\ (g_i, f_i)): i \in \{1, 2, \ldots. p_c\}$

// Restore the special and overall best of the particle
if $e(g_j, f_J(m)) < e\ (g_j, a_J\ (m))$ then
$a_{DM}\ (m+1) = f_J\ (m)$
else $a_{DM}\ (m+1) = a_j\ (m)$

if $e\ (g_j, f_J\ (m)) < e(g_j, a_J\ (m))$then
$c_J\ (m+1) = f_J\ (m)$
else $c_J\ (m+1) = c_j\ (m)$
// Restore the velocity and the position
$m = m + 1$
$f_i\ (m + 1) = f_i\ (m) + \delta f_i\ (m)$
// Find the closest data point for each particle
$\left| DMf^{min}\ (m)\ Jf^{min} \right| = \min\ (DM, i)$
// Find the particle for each data point
$\left| DMg^{min}\ (m)\ Jg^{min} \right| = \min\ (DM, i)$
// Update $a_i\ (m)$, $c_i\ (m)$
// $a_i\ (m)$ – best position,
//$c_j\ (m+1)$ – closest to the input pattern
for (i =1 to m)
if DM f_i min (m) < DM f_i min (m-1) then
$a_i(m+1) = f_{Jx}$ min (m)
else $a_i(m+1) = a_i\ (m)$
loop
// If the condition satisfies the criteria, no change in the cluster centroid, otherwise aj (m) is updated. //
for (i = 1 to m)
if DM f_j min (m) < DM f_j min (m-1) then
$c_j(m+1) := f_{Jy}$ min (m)
else $c_j(m+1) := a_j\ (m)$
loop
for (i =1 to m)
if $f\ t\ (f_i\ (m): \prod i) < f\ t\ (S(m))$then
$S\ (m+1) = f_i\ (t): \prod i$
else
$S\ (m+1) = S\ (m)$
// Find the winning particle
$f_{win}\ (m) = f\ (m) \in \min\ (e\ (a_i\ (m) - f_i\ (m))): \Pi i$
for (i = 1 to f)
// obtain the elements of the centroid cluster
$g_i^{cluster} = \Pi g \in f_i(m)$
$C_i = size\ (g_i^{cluster})$ *//Compute the updated position*
loop
$m = m + 1$

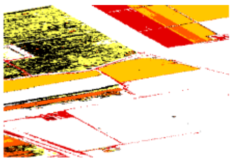
5. Experimental Results

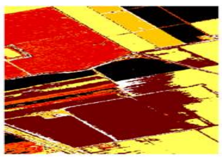
The fulfillment of EEOC algorithm is analyzed and experimented with various cluster methods such as FKM, FWKM, and FSKM. It is applied in hyperspectral scenes. Its dispatch is noticed to be passable in terms of depletion in the time complexity and the coherence of each position update. The results are commonly compared with maximum iteration fifty in EEOC worked in MATLAB v 10.

5.1. Output

5.1.1. FAST K-MEANS (FKM) Based PSC-EEOC Segmentation

Figure 2-a, portray the segmentation result for hyperspectral scene Salinas is examined in FKM based on PSC (EEOC). Figures 3-a, 4-a and 5-a depict the segmentation result for hyperspectral scene Indian Pines, Pavia University and Salinas A respectively. The analysis report for this method is portrays in Table 1. There are seven enlightenment classes in the given data sets: Roofs, Roads, Paths, Shadows, Water, Rock and Grass in the above data set. Seven clusters are sculpted as a result.


a) FKM + PSC (EEOC).


b) FWKM + PSC (EEOC).

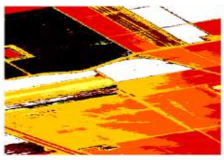
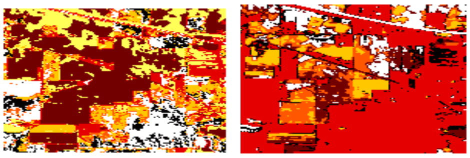
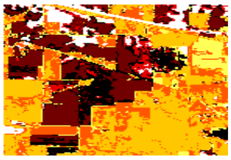

c) FSKM + PSC (EEOC).

Figure 2. Results for Salinas.

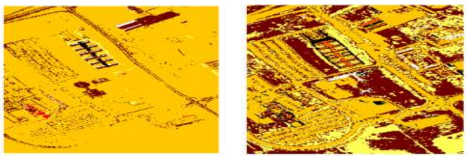


a) FKM + PSC (EEOC). b) FWKM + PSC (EEOC).



c) FSKM + PSC (EEOC).

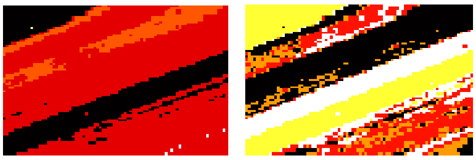
Figure 3. Result for Indian Pines.



a) FKM + PSC (EEOC). b) FWKM+PSC (EEOC).

c) FSKM+PSC (EEOC).

Figure 4. Result for Pavia University.



a) FKM + PSC (EEOC). b) FWKM + PSC (EEOC).

c) FSKM + PSC (EEOC).

Figure 5. Result for Salinas A.

5.1.2. Fast K-Means-Weight (FWKM) Based PSC-EEOC Segmentation

Figures 2-b, 3-b, 4-b, and 5-b, depict the segmentation result for FWKM based on PSC (EEOC) which is examined in hyperspectral scene. The analysis report for the above method is portrays in Table 2. Seven clusters are sculpted as a result with seven enlightenment classes.

5.1.3. Fast K-Means with Careful Seeding (FSKM) Based PSC-EEOC Segmentation

Figures 2-c, 3-c, 4-c and 5-c, depict the segmentation result for FSKM based on PSC is examined in hyperspectral scenes. The analysis report for the above method is illustrated in Table 3.

5.2. Performance and Analysis

5.2.1. Analysis for Salinas Image

Table 1 Illustrate that the Salinas image has segmented with seven clusters having number of pixels for FKM +PSC, FWKM + PSC, and FSKM +PSC.

Table 1. Analysis for salinas's image.

Number of Cluster	FKM + PSC (EEOC)	FWKM +PSC (EEOC)	FSKM + PSC (EEOC)
	Pixels	Pixels	Pixels
1	10655	15592	20876
2	130	34914	5705
3	7136	19273	15860
4	4940	4908	22128
5	11968	5358	28298
6	10957	26750	3281
7	65318	4309	14956

5.2.2. Analysis for Indian Pines

Table 2, illustrate that the Indian Pines scene has segmented with seven clusters having number of pixels for those methods. However, FWKM based on PSC has null value in sixth cluster.

Table 2. Analysis for Indian Pines.

Number of Cluster	FKM + PSC (EEOC)	FWKM +PSC (EEOC)	FSKM + PSC (EEOC)
	Pixels	Pixels	Pixels
1	1556	1797	2611
2	6841	24922	3930
3	2509	10905	776
4	1107	2113	3790
5	2249	1709	6535
6	3317	0	1854
7	3446	2009	1529

5.2.3. Analysis for Salina's _A

Table 3 Illustrate that the resultant of Salinas scene. It paves six clusters has segmented for FSKM, whereas the others has cluster as seven. Despite having seven clusters, the FWKM+PSO have three null clusters. Likewise, FKM+PSO have two null clusters and one cluster has single pixel.

Table 3. Analysis for salinas A.

Number of Cluster	FKM + PSC (EEOC)	FWKM +PSC (EEOC)	FSKM + PSC (EEOC)
	Pixels	Pixels	Pixels
1	1812	1795	1479
2	0	2365	2169
3	4629	0	940
4	686	0	921
5	0	0	0
6	1	1355	1629
7	10	1623	------

5.2.4. Analysis for Pavia University

Table 4, Illustrate the resultant of Pavia University scene has seven clusters with number of pixels for FKM+PSC, FWKM+PSC and FSKM+PSC methods.

Table 4. Analysis for pavia university.

Number of Cluster	FKM+PSC (EEOC)	FWKM+PSC (EEOC)	FSKM+PSC (EEOC)
	Pixels	**Pixels**	**Pixels**
1	1135	1878	2338
2	16215	3798	23336
3	966	1161	2167
4	1000	286	104013
5	183440	1363	5198
6	3439	198131	2471
7	1205	783	67877

Table 5 Illustrate that the comparison of FKM +PSC, FWKM+PSC, and FSKM+PSC for hyperspectral scene in terms of elapsed time and fitness value. The minimum fitness value indicated the optimum result. For all four images the fitness value and elapsed time in FWKM are optimum.

Table 5. Comparison of FKM+PSC, FWKM+PSC, FSKM+PSC.

INPUT	SIZE	FKM + PSC (EEOC)		FWKM +PSC (EEOC)		FSKM + PSC (EEOC)	
		ELAPSED TIME IN SECONDS	FITNESS VALUE	ELAPSED TIME IN SECONDS	FITNESS VALUE	ELAPSED TIME IN SECONDS	FITNESS VALUE
SALINAS_A	83x86x204	97.456s	80.24E+05	97.814s	46.96E+05	99.786s	47.54E+05
INDIAN PINES	145x145x200	274.564s	13.75E+06	272.543s	13.73E+06	285.447s	13.47E+06
SALINAS	512x217x204	1487.234 s	72.04E+06	1292.657s	52.43E+06	1440.654s	69.00E+06
PAVIA UNIVERSITY	610x340x103	2818.794s	34.08E+07	2763.612s	21.11E+07	2850.741s	32.65E+07

5.3. Comparison of FKM+PSC, FWKM+PSC, FSKM+PSC

The below bar charts portray the elapsed time in different method (Figure 6) and fitness value of different methods (Figure 7). The elapsed time and fitness value has taken from the Table 5.

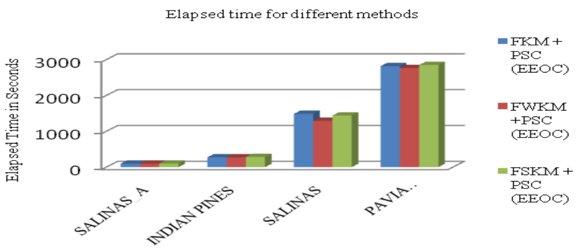


Figure 6. Elapsed Time chart.

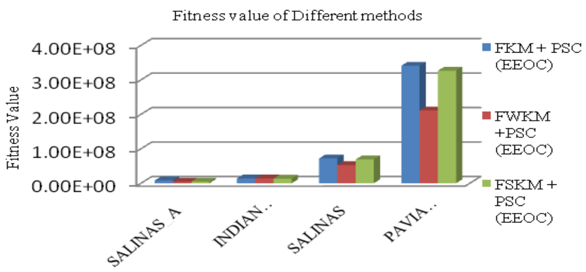


Figure 7. Fitness value chart.

Table 6 illustrates the result of various analysis methods namely Jaccard, Dice, Tanimoto, and its Accuracy. It is constructed by compare the resultant image with their ground truth data. As a whole, the EEOC worked with various clustering method produce efficient result

Table 6. Result of various analysis method.

INPUT	AnalysisMethod	FKM+ PSC EEOC	FWKM+PSC EEOC	FSKM+PSC EEOC
Salinas	Jaccard	0.9181	0.9467	0.9347
	Dice	0.9190	0.9483	0.9373
	Tanimoto	0.9181	0.9467	0.9347
	Accuracy	0.9181	0.9467	0.9347
Salinas _A	Jaccard	0.9255	0.9450	0.9356
	Dice	0.9277	0.9475	0.9378
	Tanimoto	0.9255	0.9450	0.9356
	Accuracy	0.9255	0.9450	0.9356
Indian Pines	Jaccard	0.9217	0.9478	0.9360
	Dice	0.9258	0.9489	0.9380
	Tanimoto	0.9217	0.9478	0.9360
	Accuracy	0.9217	0.9478	0.9360
Pavia University	Jaccard	0.9099	0.9496	0.9299
	Dice	0.9043	0.9498	0.9299
	Tanimoto	0.9099	0.9496	0.9299
	Accuracy	0.9099	0.9496	0.9299

6. Conclusions

This paper has focused on hyperspectral satellite images. The light weight swarm clustering solution entitled as Enhanced Estimation of Centroid (EEOC) has performed. The unsupervised method such as FKM, FWKM, and FSKM methods has examined with EEOC. It has materially quickened restoration time. The hyperspectral bands are clustered based on feature matrix and a band which has pinnacle variance from each cluster is picked out. Segmentation is carried out by PSC-EEOC. To be crisp, FWKM with PSC-EEOC produce the best result in terms of time complexity and fitness values for Salinas's scene, Salinas A scene and Pavia University. For Indian Pines, despite having time complexity is exorbitant, FSKM method produce elite result based on fitness value. Crystal clearly, FWKM approaches yields peerless result which compare with other panorama in all aspects. Despite segmenting properly, most of these methods are lead over segmentation. In spite of being time reduction, EEOC takes more time to execute. For future enhancement, hybrid segmentation technique will be developed which reduce the execution time. Besides, classification will be carried out by mapping resultant data with their ground truth data.

References

[1] Arthur D. and Vassilvitskii S., "K-means++: The Advantages of Careful Seeding," *in Proceedings of the 8th Annual ACM-SIAM Symposium on Discrete Algorithms*, New Orleans, pp. 1027-1035, 2007.

[2] Celik T., "Unsupervised Change Detection in Satellite Images Using Principle Component Analysis and K-Means Clustering," *IEEE Geoscience and Remote Sensing Letters*, vol. 6, no. 4, pp. 772-776, 2009.

[3] Khodadazadeh M., Li J., Plaza A., Ghassemian H., Bioucas-Dias J., and Li X., "Spectral-Spatial Classification of Hyperspectral Data using Local and Global Probabilities for Mixed Pixel

Characterization," *IEEE Geoscience and Remote Sensing*, vol. 52, no. 10, pp. 6298-6314, 2014.

[4] Li J., Bioucas-Dias J., and Plaza A., "Spectral-Spatial Hyperspectral Image Segmentation Using Subspace Multinomial Logistic Regression and Markov Random Field," *IEEE Geosciences and Remote Sensing*, vol. 50, no. 3, pp. 809-823, 2012.

[5] Li J., Bioucas-Dias J., and Plaza A., "Hyperspectral Image Segmentation Using A New Bayesian Approach with Active Learning," *IEEE Geoscience and Remote Sensing*, vol. 49, no. 10, pp. 3947-3960, 2011.

[6] Mohsen F., Hadhoud M., Mostafa K., and Amin K., "A New Image Segmentation Method Based on Particle Swarm Optimization," *The International Arab Journal of Information Technology*, vol. 9, no. 5, pp. 487-493, 2012.

[7] Plaza A., Benediktsson J., Boardman J., Brazile J., Bruzzone L., Camps-Valls G., Chanussot J., Fauve M., GambaP., Gualtieri A., Marconcini M., Tilton J., and Trianni G., "Recent Advances in Techniques for Hyperspectral Image Processing," *Remote Sensing of Environment*, vol. 113, supplement. 1, pp. s110-s122, 2009.

[8] Plaza A., Valencia D., Plaza J., and Martinez P., "Commodity Cluster-Based Parallel Processing of Hyperspectral Imagery," *Journal of Parallel and Distributed Computing*, vol. 66, no. 3, pp. 345-358, 2006.

[9] Song B., Li J., Mura M., Li P., Plaza A., Bioucas-Dias J., Benediktsson J., and Chanussot J., "Remotely Sensed Image Classification using Sparse Representations of Morphological Attribute Profiles," *IEEE Geoscience and Remote Sensing*, vol. 52, no. 8, pp. 5122-5136, 2014.

[10] Tarabalka Y., Benediktsson J., and Chanussot J., "Spectral-Spatial Classification of Hyperspectral Imagery Based On Partitional Clustering Techniques," *IEEE Geoscience and Remote Sensing*, vol. 47, no. 8, pp. 2973-2987, 2009.

[11] Theiler J. and Gisler G., "Contiguity-Enhanced K-Means Clustering Algorithm for Unsupervised Multispectral Image Segmentation," *in Proceedings SPIE 3156, Algorithms, Devices and System for Optical Information Processing*, San Diego, pp. 108-118, 1997.

[12] Veligandan S., Prakasam S., Rengasari N., and Kavitha M., "Multiband Image Segmentation by using Enhanced Estimation of Centroid (EEOC)," *Information Journal-Japan*, vol. 17, no. 6, pp. 1967-1980, 2014.

[13] Veligandan S. and Rengasari N., "A Survey of Hyperspectral Image Segmentation Techniques for Multiband Reduction," *Australian Journal of Basic and Applied Sciences*, vol. 9, no. 7, pp. 446-451, 2015.

[14] Veligandan S. and Rengasari N., "Hyperspectral Image Segmentation Based on Particle Swarm Optimization with Classical Clustering Methods," *Advances in Natural and Applied Sciences*, vol. 9, no. 12, pp. 45- 53, 2015.

[15] Veligandan S. and Rengasari N., "Segmentation of Hyperspectral Image using JSEG based on Unsupervised Clustering Algorithms," *ICTACT Journal on Image and Video Processing*, vol. 6, no. 2, pp. 1152-1158, 2015.

[16] Yassine I. and Belfkih S., "Texture Image Segmentation Using A New Descriptor and Mathematical Morphology," *The International Arab Journal of Information Technology*, vol. 10, no. 2, pp. 204-208, 2013.

Saravana Kumar Veligandan is a research scholar in Manonmaniam Sundaranar University, Tirunelveli, Tamilnadu, India. He received his M.Sc., [Statistics] and M.Tech [Computer and Information Technology] from same University. He was a faculty in the department of Computer Science and Engineering, as Asst. Prof in SCAD College of Engineering & Tech and Jayamatha Engineering College. At present he is working as Faculty in Centre for Bioinformatics, Pondicherry University. His area of interest is Image Processing, Pattern Recognition and Data mining.

Naganathan Rengasari is a Professor in the Department of Computer Science and Engineering, Hindustan University, Chennai, India since June 2012. He was a faculty at various levels in the Department of Computer Science and Engineering, Alagappa University, Karaikudi, Tamilnadu, India during 1986-2008 and other Institutions between 2008-2012. He has received M.Sc. [Applied Mathematics] from Madurai Kamaraj University, India; M.Tech. [Computer and Information Technology] from Manonmaniam Sundaranar University, India and Ph.D. in Computer Applications from Alagappa University. His area of interests is Network Security, Information Security, Algorithm, and Data Mining. He has 78 research publications to his credit in International/ National Journals/Conferences. He is a member of ACM, IET, CSI, ISTE, and ACCS.