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SEGMENTATION OF HYPERSPECTRAL IMAGE USING JSEG BASED ON UNSUPERVISED CLUSTERING ALGORITHMS

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Abstract

Hyperspectral image analysis is a complicated and challenging task due to the inherent nature of the image. The main aim of this work is to segment the object in hyperspectral scene using image processing technique. This paper address a novel approach entitled as Segmentation of hyperspectral image using JSEG based on unsupervised cluster methods. In the preprocessing part, single band is picked out from the hyperspectral image and then converts into false color image. The JSEG algorithm is segregate the false color image properly without manual parameter adjustment. The segmentation has carried in two major stages. To begin with, colors in the image are quantized to represent several classes which can be used to differentiate regions in the image. Besides, hit rate regions with cognate color regions merging algorithm is used. In region merging part, K-means, Fuzzy C-Means (FCM) and Fast K-Means weighted option (FWKM) algorithm are used to segregate the image in accordance with the color for each cluster and its neighborhoods. Experiment results of above clustering method could be analyzed in terms of mean, standard deviation, number of cluster, number of pixels, time taken, number of objects occur in the resultant image. FWKM algorithm results yields good performance than its counterparts.

Keywords:

Cluster, Region Growing, Hit Ratio Region, Class-Map, Quantize

1. INTRODUCTION

A hyperspectral image is a high-dimensional image set that quintessentially comprise of 100-200 image Channels. Each channel is a gray scale image that indicates the spectral riposte to a precise frequency in the electromagnetic spectrum. These frequencies usually encompass the visible spectrum of light; howbeit most of the channels are concentrated in the infrared range. This empowers a hyperspectral image to divulge features that are not perceptible in a conventional color image. Each pixel in the image will have a spectral riposte vector that is the high-dimensional tantamount of the pixel's color. The accurate segmentation and classification of remote sensing images is a monumental task for copious practical applications, such as precision mining, agriculture field, detecting war ship, monitoring submarine, and detecting chemical weapons. The advent and growing availability of hyperspectral imagery, which records hundreds of spectral bands, has opened new possibilities in image analysis and classification. Thus, every pixel in a hyperspectral image contains values that correspond to the detailed spectrum of reflected Light. This rich spectral information in every spatial location increases the capability to distinguish different physical materials and objects leading to the potential of a meticulous image classification. An extensive literature is available on the segmentation of hyperspectral images where a wide range of pixel-level processing techniques is proposed. i.e., techniques that assign each pixel to one of the classes based on its spectral values.

Image segmentation is one of the concepts in image processing to analysis and used in myriad applications. Color image segmentation plays a vital role in many areas, especially in medical field and remote sensing field. From the segmentation results, it is possible to identify the region of interest and objects needed for our analysis in the image. Recently, plethora techniques are employed in image segmentation. For example, stochastic model based approaches [4], morphological watershed based region growing [10], K-means clustering, [12], graph partitioning [11] etc. The image region of interest extraction in the object-oriented image compression and content-based image retrieval [4] is illustrated. In these applications, image segmentation is usually used for image analysis, identification and compress code, etc. Color images with homogeneous regions are segmented with an algorithm is to generate Clusters in the color space for segmenting the color images with homogeneous region [6]. The spatial arrangement of pixels using a region-growing is one of the techniques to segment images with texture whereby a homogeneity mode is defined with pixels conglomeration in the segmented region. In order to segment images, one of consider that different scales of image. Here, unsupervised colour-texture regions segmentation is ideal. It tests the homogeneity of a given colour-texture pattern which is computationally more feasible than model parameter estimation. Hyperspectral scene can segment by enhanced estimation of centroid [14] has explained. In [15], a survey of hyperspectral image segmentation techniques for multiband reduction is illustrated. A novel method [16] proposed to segment the nucleus in cytoplasm using arithmetic and automatic threshold concept. Over segmentation, spoil the segmentation accuracy. Color image segmentation method [17] considering pair-wise color projection is proposed. Here the over segmentation is occurred due to superposition process.

In this paper, we deal with hyperspectral image segmentation based on JSEG worked on different unsupervised clustering algorithms. Thus, most of the channels are focused in the infrared range in hyperspectral image; the first one third of the hyperspectral image contains blue whereas second part filled with green and last part covered with red channels. We pick out single band from mid of first part (blue) and convert into false color. The segmentation of false color images is properly performed, without manual parameter adjustment for Pavia University image and simplifies texture and color. This method consists of two phase. In the first phase, color quantization is carried out. In the second phase, spatial segmentation is carried out.

2. THE PROPOSED WORK

The JSEG method is applied in single band of hyperspectral scene, worked with various unsupervised method such as K-Means, FCM and FWKM. Besides, we analysis the result and conclude which method produces the magnified result. To begin, the hyperspectral data is read out. Single band from mid of first part could be picked out from the hyperspectral data and convert into false color. Colors in the image are roughly quantized without materially degrading the color quality. The aim is to analects a few representing colors which can be determined to differentiating proximate regions in the image. A magnificent color quantization expertise is indispensible for the segmentation process and quantized image is segmented using JSEG worked with different unsupervised algorithms.

The Fig.1 depicts the proposed method. Here, unsupervised segmentation method is utilized. This segmentation method is to extract archetypal colors differentiating proximate regions in the acquired image. To smooth the image and existing noise, the color quantization using peer group filtering is applied through perceptual weighting on individual pixels. Then new values that point outing the smoothness of the local areas are obtained, and a weight is assigned to each pixel, prioritizing textured areas to smooth areas. These areas are pinpointed with a quantization vector to the pixel colors, based on General Lloyd Algorithms (GLa), which the perceptually uniform L*u*v color space is adopted, presenting the overall distortion D:

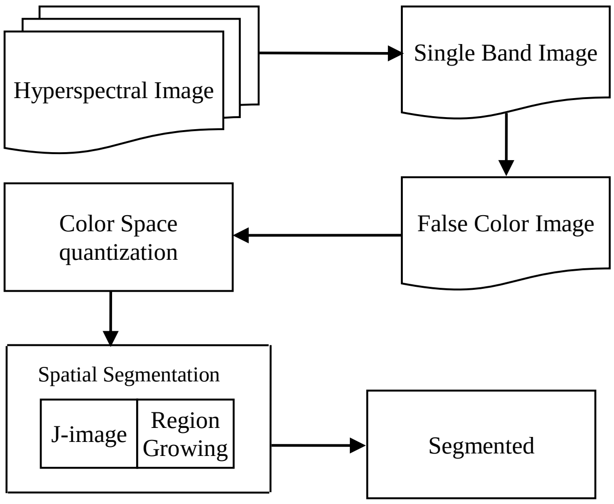

Fig.1. The flow of proposed method

$$D = \sum iD_i = \sum i \sum nv(n)\|x(n) - ci\|2x(n) \in c_i \tag{1}$$

and it is derived for

$$c_i = \frac{\sum v(n) \times (n)}{\sum v(n)} x(n) \in c_i \tag{2}$$

where, c_i is the centriod of cluster C_i, $x(n)$ and $v(n)$ are the color vector and the perceptual weight for pixel n. D_i is the total distortion for C_i.

L*a*b color space enables as to quantify the visual differences. The L*a*b space consists of luminosity layer 'L*', chromaticity-layer 'a*' indicating where the color falls along the red-green axis and chromaticity-layer 'b*' indicating where the color falls along the blue-yellow axis. All of the color information is in the 'a*' and 'b*' layers. We can measure the difference between two colors using the Euclidean distance metric. Classify the color in 'a*' and 'b*' using clustering method.

After cluster merging for color quantization, a label is assigned for each quantized color, delineating a color class for image pixels quantized to the concordant color.

2.1 J-VALUE

All mandatory segmentation information, after color quantization, is extracted and relocated to a class-map [4]. A peculiar region contains pixels from a color class set, which is distributed in image regions. These regions, forming each one, a class-map has distributed points in all spatial data segments [2], corresponding a two-dimensional plane, and represents the Cartesian position vector (x, y). In order to calculate the J-value, Z is defined as the set of all points of quantized image, then $z = (x, y)$ with $z \in Z$ and being 'm' the average in all Z elements. C is the number of classes obtained in the quantization. Then Z is classified into C classes, Z_i are the elements of Z belonging to class i, where $i = 1,\ldots,C$ and 'm_i' are the elements averages in Z_i.

$$m = \frac{1}{N}\sum Z \in zZ \tag{3}$$

$$mi = \frac{1}{Ni}\sum z \in zZ \tag{4}$$

The J-Values are computed as follows:

$$J = \frac{SB}{SW} = \frac{(ST - Sw)}{Sw} \tag{5}$$

where,

$$ST = \sum_{z \in Z}\|z - m\|^2 \tag{6}$$

$$SW = \sum_{i=1^*}^{c}\sum_{z \in Z}\|z - mi\|^2 \tag{7}$$

The parameter ST represents the sum of quantized image points within the average in all Z elements. Thereby, the relation between SB and SW, denotes the measures of distances of this Class relation, for arbitrary nonlinear class distribution. J for higher values indicates with homogeneous color regions. The distance and consequently, the J value, decrease for images with uniformly color classes. Each segmented region could be recomputed, instead of the entire class-map, with new parameters adjustment for J average. J_k represents J calculated over region K, M_k is the number of points in K, and N is the total number of points in the class-map, with all regions in class-map summation.

$$J = \frac{1}{N}\sum_k M_k J_k \tag{8}$$

For a fixed number of regions, a criterion for J is intended for lower values.

3. SPATIAL SEGMENTATION ALGORITHM

The characteristics of the J-images allow us to use a region-growing method to Segment the image. Here cluster approaches are used.

3.1 K-MEANS ALGORITHM

K-means algorithm [12] is a non-fuzzy clustering method whereby each pattern can only belong to one centre at any one time. Let $X = \{x_1, x_2, \ldots x_n\}$ present a set of data, where n is the number of data points $V = \{v_1, v_2, \ldots v_n\}$ is the corresponding set centers, where c is the number of clusters. The aim of K-means algorithm is to minimize the objective function $J(V)$, in this case a squared error function:

$$J(V) = \sum_{i=1}^{c} \sum_{j=1}^{c_1} \left\| x_{ij} - v_j \right\|^2 \tag{9}$$

where, $\left\| x_{ij} - v_j \right\|$ is the Euclidean distance between x_{ij} and v_j. c_i is the number of data points in the cluster i. The i^{th} centre v_i can be calculated as:

$$v_i = \frac{i}{c_i} \sum_{j=1}^{c_i} x_{ij},\ i = 1 \ldots c \tag{10}$$

The procedure of this algorithm can be described as followed:

1. Randomly select c cluster centers.
2. Calculate the distance between all of the data points and each centre.
3. Data is assigned to a cluster based on the minimum distance.
4. Recalculate the centre positions using step 2.
5. Recalculate the distance between each data point and each centre.
6. If no data was reassigned, then stop, otherwise repeat step 3.

3.2 FAST K-MEANS (WEIGHTED) ALGORITHM [FWKM]

The classical k-means algorithm [12] is a fast method to perform clustering. The algorithm consists of a simple re-estimation procedure.

Input: A set of n data points, and the number of clusters (K)

Output: centroids of the K cluster

1. Initialize the K cluster centers
2. Repeat Assign each data point to its nearest cluster center
3. Recomputed the cluster centers using the current cluster memberships
4. Until there is no further change in the assignment of the data points to new cluster centers.

The original n data points to be clustered are contained in the data set = $\{x_1, \ldots, x_n\}$. The k-means algorithm partitions n data points into K sets. The assignment of a data point x_i to its nearest cluster center c_j (step 2) is decided on the basis of the membership function, $m(c_j \mid x_i)$.

The function returns either one of the {0, 1} values:

$m(c_j \mid x_i) = 1$ if j = argmin $K \|x_i - c_j\|2$ it is zero, otherwise.

In step 3, the new centroid of clusters can be computed from all data points x_i in the cluster. The objective function J of the algorithm is to minimize the sum of error squared. In K-means algorithm every data point has equal importance in locating the centroid of the cluster. This property does no longer hold in the case of density-based sample clustering, for which each data points represents varied density in the original data. Therefore, the clustering algorithm has to consider a weight associated with each data point in the computation of cluster centers. This algorithm is entitled as Fast K-means (weighted) algorithm. [13].

Input: a set of n data points obtained from the density-biased reservoir sampling, and the Number of clusters (k)

Output: centroids of the K clusters

1. Initialize the K cluster centers
2. Repeat

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

$$m(c_j | x_i) = \frac{\left\| x_i - c_j \right\|^{-p-2}}{\sum_{j=1:k} \left\| x_i - c_j \right\|^{-p-2}} \tag{11}$$

3. For each center c_j, recomputed the cluster center c_j using the current cluster memberships and weights,

$$c_j = \frac{\sum_{i=1:n} m(c_j \mid x_i) w(x_i) x_i}{\sum_{i=1:n} m(c_j \mid x_i) w(x_i)} \tag{12}$$

   where, $w(x_i)$ is a weight associated with each data point

4. Until there is no reassignment of data points to new cluster centers.

Howbeit, the weight function in our algorithm is introduced for the different purpose. It represents the density of the original data points.

3.3 FUZZY C-MEANS ALGORITHM [FCM]

The FCM algorithm, also known as Fuzzy ISODATA, is one of the most generally used methods in pattern recognition. It is based on the minimization of the objective function Eq.(13) to achieve a magnificent classification. $J(U, V)$ is a squared error clustering criterion, and solutions of minimization of Eq.(3) are least-squared error stationary points of $J(U, V)$.

$$J(U,V) = \sum_{i=1}^{n} \sum_{j=1}^{c} (\mu_{ij})^m \left\| x_i - v_j \right\|^2 \tag{13}$$

Once again, the expression $x = \{x_1, x_2, \ldots x_n\}$ is a collection of data, where n is the number of data points and $v = \{v_1, v_2, \ldots v_c\}$ is the set of corresponding cluster centers in the data set X, where c is the number of clusters. Is the membership degree of data xi to the cluster centre x_i. Meanwhile, v_j satisfy the following conditions:

$$\mu_{ij} \in [0,1], \forall_i = 1, \ldots, n, \forall_j = 1, \ldots, c \tag{14}$$

$$\sum_{j=1}^{c} \mu_{ij} = 1, \forall_i = 1, \ldots, n \tag{15}$$

$U = (\mu_{ij})n*c$ is a fuzzy partition matrix $\|x_i - v_j\|$ means the Euclidean distance between x_i and v_j. Parameter m is called the “fuzziness index”, it is used to control the fuzziness of memberships of each datum. The value of m should be within the range m [1, ∞] .There is no theoretical basis for the optimal selection of m, but value of m is 2.0 usually chosen. The FCM algorithm can be performed by following steps.

1. Initialize the cluster centers = $\{v_1, v_2,\ldots, v_c\}$ or initialize the memberships matrix with random value, and make sure it satisfies conditions Eq.(4) and Eq.(5), then calculate the centers
2. Calculate the fuzzy membership using

$$\mu_{ij} = \frac{1}{\sum_{i=0}^{n}\left(\frac{d_{ij}}{d_{ik}}\right)^{\frac{2}{m-1}}} \tag{16}$$

3. Compute the fuzzy center vj using

$$v_j = \frac{\sum_{i=1}^{n}(\mu_{ij})^{m_{x_i}}}{\sum_{i=1}^{n}(\mu_{ij})^{m}}, \forall_j = 1,\ldots,c \tag{17}$$

4. Repeat step 2 to 3 until the minimum j value is achieved.

Algorithm:

a. Read the hyperspectral image as input image;
b. Pick out one band;
c. Convert into false color image;
d. Convert RGB to L*a*b;
e. Apply color quantization algorithm
f. Find J-value
g. Apply K-means algorithm or Fuzzy C-Means or FWKM.
   i. Perform region growing and region merging process.
h. Display the segmented image.

3.4 VALLEY DETERMINATION

A set of small initial areas are determined as the base for region growing. These areas have the lowest local j values simply called as valleys. A heuristics for the valley determination presupposed a condition for initial regions to be determined as the pattern growing.

As follows:

1. Calculate the average and the standard deviation of the local j values in the region, denoted by σ_j and μ_j respectively.
2. Set a threshold T_j at

$$T_j = \mu_j + \alpha\sigma_j$$

The condition to candidate valley points for pixels with local J values is determined $T_j > j$. Connect the points based on the 4-connectivity and obtain the valleys.

   a. For candidate valleys smaller than the spatial segmentation relation between scale and Image size, they are denoted as valleys.
   b. A present parameter values [-0.6, -0.4, -0.2, 0, 0.2, 0.4] is given for variable, which gives the most number of valley.

3.5 VALLEY GROWING

The new regions are then grown from the valleys. It is slow to grow the valleys pixel by pixel. A faster approach is used in the implementation:

1. Remove "holes" in the valleys.
2. Average the local J values in the remaining non segmented part of the region and Connect pixels below the average to form growing areas. If a growing area is adjacent to one and only one valley, it is assigned to that valley.
3. Calculate local J values for the remaining pixels at the next smaller scale to more accurately locate the boundaries.
4. Grow the remaining pixels one by one at the smallest scale. Unclassified pixels at the Valley boundaries are stored in a buffer. Each time, the pixel with the minimum local j value is assigned to its adjacent "valley" and the buffer is updated till all the pixels are classified.

3.6 REGION MERGE

An initial segmentation of the image is obtained by applying region growing. It often has over segmented regions. These regions are merged based on their color similarity. The quantized colors are naturally color histogram bins. The color histogram features for each region are analects and the distances between these features can be calculated. Since the colors are very coarsely quantizes, in this algorithm it is assumed that there are no correlation between the quantized colors. Therefore, a Euclidean distance measure is applied directly. First, distances between two neighboring regions are calculated and stored in a distance table. The pair of regions with the minimum distance is merged together. The color feature vector for the new region is calculated and the distance table is updated. The process continues until a maximum threshold for the distance is reached. After merging, the final segmentation results are obtained.

4. EXPERIMENTAL RESULTS

The JSEG algorithms with various unsupervised cluster methods are tested on a hyperspectral image (Pavia University). Single band of the hyperspectral data is picked out. We pick the mid of the first part and converted into false color. In JSEG algorithm, the user gives the three parameters. The first parameter is threshold for the color quantization process. It determines the minimum distance between two quantized colors. The second one is the number of scales desired for the image. The last one is a threshold for region merging. These parameters are necessary because of the varying image characteristics in disparate applications. The algorithm works effectively on a diversification of images using a constant set of parameter values. Segmented images are dimmed to show boundaries. Howbeit, it can be seen that the results are magnificent. This system is developed in MATLAB v10 version.

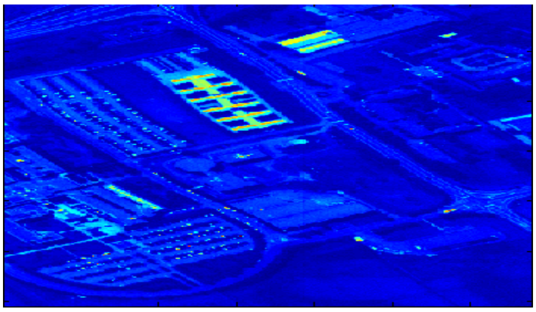

Fig.2. Input image-Pavia University (single band)

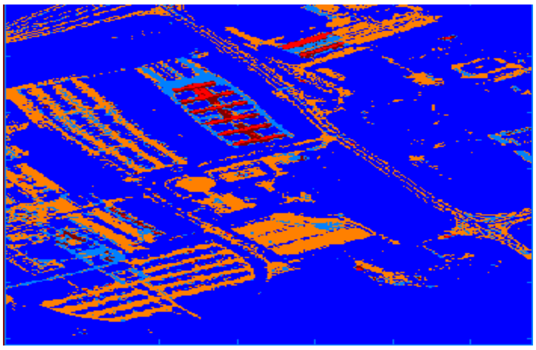

Fig.3. JSEG with K-means

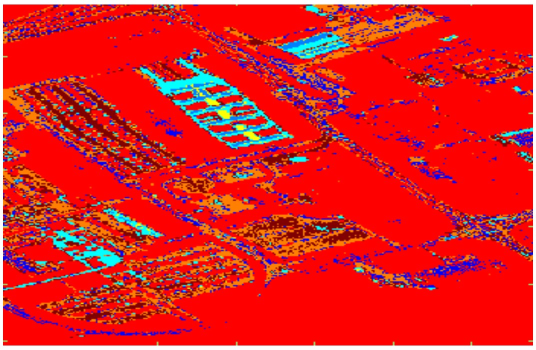

Fig.4. JSEG with Fuzzy C-Means

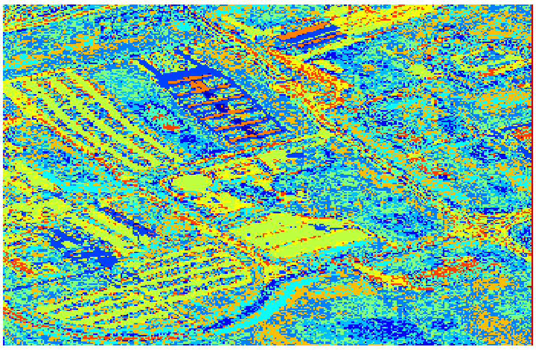

Fig.5. JSEG with FWKM

4.1 ANALYSIS

4.1.1 Output Analysis For JSEG With K-Means:

The Table.1 portrays the number of clusters and corresponding pixel occurs in that cluster constructed on JSEG worked with K-means algorithm. In this approach, image is clustered into 8 parts. Most of the pixel accumulated on cluster 1, 6, 8 and cluster number 3, 4, 5, has no pixel value. From this it can be identified that segmentation is not carried out properly.

Table.1. JSEG with K-Means

Number of Cluster	**Proposed method (K-Means)**
1	113606
2	8887
3	0
4	0
5	0
6	24710
7	1154
8	87263

4.1.2 Output analysis for JSEG with FCM:

The Table.2 portrays the number of cluster and corresponding pixel occurs in that clusters constructed on JSEG worked with Fuzzy C-Means algorithm. In this approach, image is clustered into 8 parts. Even though, the segmentation accuracy is improved, it takes more time to execute.

Table.2. JSEG with FCM

Number of Cluster	**Proposed method FCM**
1	86023
2	57851
3	1154
4	4383
5	55755
6	13282
7	8570
8	8602

4.1.3 Output Analysis for JSEG with FWKM:

The Table.3 portrays the number of cluster and corresponding pixel occurs in that cluster constructed on FWKM worked with JSEG algorithm.

Table.3. JSEG with FWKM

Number of Cluster	**Pixels**
1	86211
2	10692
3	5987
4	22037
5	15856
6	8226
7	9469
8	19738
9	17657
10	8570
11	18898
12	1131
13	8690
14	23
15	2435

In this approach, image is clustered into 15 parts. In all clustering algorithm image is segmented by means of color. When number of cluster is increased, it means that each color is segregated exactly as a cluster i.e. produce the accuracy result. Each and every object is exactly segregated in FWKM. Even the small differences in the colors are also segregated that is why it contains more clusters. From this it can be identified that the segmentation accuracy is improved.

4.2 ANALYSIS OF THE RESULT:

Table.1, Table.2 and Table.3, portray the number of pixels occurred in the resultant clusters. Table.2 depicts the comparison of JSEG worked with K-Means, FCM, and FWKM in terms of connectivity, and time taken to execute. The connectivity occur in the resultant image by various clustering method is same as 26. K-Means produce minimum time to execute this is work, whereas FCM takes more time.

Table.4. Comparative Study based on time

Image	Method	Connectivity	Time taken
Pavia University	JSEG with K-Means	26	21.6563
	JSEG with FCM	26	121.9063
	JSEG with FWKM	26	30.5313

The mean and standard deviation value of input image (Pavia University's single band) are 115.8022 and 18.0337 respectively.

Table.5. Comparative study based on Statistics

Image	Methods	Mean	Std.dev	Correlation
Pavia University	JSEG with K-Means	50.2468	42.9724	- 0. 0 209
	JSEG with FCM	143.8096	61.4535	0.493
	JSEG with FWKM	124.6709	59.8416	0.720

From the above Table.3, the mean value of FWKM is closely to mean of input images. Despite being K-Means standard deviation is least, it yields the negative correlation. Fuzzy C-Means produce mediocre result in mean, standard deviation and correlation. From that we can understand that JSEG worked with FWKM is outperformed than K-means and FCM in terms of both speed and accuracy.

5. CONCLUSION

In this work, a novel approach entitled as Segmentation of hyperspectral image based on JSEG with various unsupervised cluster methods has addressed. Single band from hyperspectral scene is picked out and converted into false color. The segregation consists of color quantization and spatial segmentation. Result shows that this approach provides magnified segregation on single band of Pavia University. To be crisp, JSEG with FWKM method segregates the image more perfectly than other methods. It segregates the given image into 15 clusters where as other methods clustered only half of it. The mean and correlation value of this approach is closely to the input image. In addition JSEG with FWKM produced outperformed results in terms of both speed and accuracy. Despite producing best result, JSEG with FWKM approach leads to over segmentation. Future research work is to handle the varying shades of an object due to illumination and segregate the boundaries of two neighbor regions clearly.

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