Unsupervised Segmentation of Multispectral Textured Images using GA-GMRF model

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Abstract— This paper proposes an hybrid genetic algorithm (GA) and Gaussian Markov random field model (GMRF) based method for segmentation of multi-spectral textured images. It also evaluates the popular unsupervised image segmentation approaches, Genetic algorithm based clustering and simple Gaussian Markov random field model with the hybrid GA-GMRF method for high spatial resolution textured imagery. Each method is described and the compatibility of each method with the textured image is examined. It is observed that GA based clustering is more suitable for medium resolution imagery and for images without textures. GMRF model which gives desirable results for textured images requires several iteration steps to approximate near optimal solutions. The hybrid GA-GMRF method, in which the powerful global exploration of GA is used to initialize the ICM algorithm, has found more promising and gives improved results in terms of both accuracy and time complexity than the two other methods for multi-spectral textured images.

Keywords - Unsupervised image segmentation, Genetic algorithm, Markov random fields, texture, high spatial resolution multi-spectral images

1. Introduction

Image classification is a task that classifies pixels of an image using different labels so that the image is partitioned into non overlapping labeled regions. Land cover classification is one of the fundamental operations in the arena of multi-spectral image analysis. This is for the reason that classification results are the basis for many environmental and socio economic applications at global, regional and even local level. However deriving land cover information from multi-spectral imagery is a difficult task because of the complexity of the landscape and the spatial as well as spectral resolution of the imagery being used [1]-[2]. Coarse spatial resolution data are preferable at continental or global scale. At regional level, medium spatial resolution imagery is often used and for classification at local level, high spatial resolution data are helpful. Multispectral data at moderate and coarse spatial resolution can be differentiated based on the spectral reflectance patterns. At high spatial resolution the role of texture assumes more significance. Although a large number of segmentation techniques are available in the literature for classification, there is no standard criterion on, which method is more suitable or more effective. The segmentation problem is addressed as supervised and unsupervised segmentation. When the number of classes, image labels and model parameters are unknown, it is completely unsupervised. If the number of classes is known then it is partially unsupervised.

When the image is of low or medium resolution and the number of classes is known *a priori*, among the several unsupervised classification techniques, K- means algorithm is one of the most widely used ones. But it has a limitation that it gets stuck at sub optimal solutions depending on the choice of initial cluster centers [3], [4]. Genetic algorithm (GA) is a stochastic search technique based on the mechanics of natural selection and genetics originated from the imitations of natural evolutions on the earth. This has been successfully employed in the classification of artificial as well as real image data sets in [3]. They work with the strings that encode candidate solutions called chromosomes and collection of such chromosomes is known as population. An objective and fitness function that represents the degree of goodness of the string is associated with each string. This fitness function is used to guide the stochastic selection of the chromosomes which are then utilized to generate new candidate solutions through crossover and mutation. Crossover allows solutions (chromosomes) to exchange information and produce new chromosomes. Mutation is used to randomly change the value of genes and increase the diversity in the population.

With high spatial resolution imagery, the objects make up the thematic classes as the spectral resolution of the sensor nears the object size on the ground and thus brings in the texture effects. This limits the potential of spectral information since same spectral reflectance value can correspond to different objects. Hence the contextual classifiers that utilize both spectral and spatial information are particularly worthful for fine resolution [5]-[6]. Zoltan Kato and Ting-Chuen Pong [7] proposed an MRF model based image segmentation method which aims at combining colour texture features which relies on Bayesian estimation via combinatorial optimization. The algorithm is highly parallel. Brandt C.K Tso and Paul M. Mather [8] presented an MRF model using Genetic algorithms for multi source remote sensing imagery. As Markov random field (MRF) model utilizes both spectral and spatial information to model the local structure of an image, it is undoubtedly, a potent mathematical tool for contextual modeling of spatial data [2], [9], [10]. For modeling textures, spatial interaction models particularly conditional Markov models are more useful. GMRF are a special case of Markov random fields used to model textured images [9], [11], [12]. GMRF model representing colour texture that takes into account both within band and between bands interaction has been proposed and successfully implemented by Panjwani and Healey [11]. In MRF based segmentation, the most popular criterion for optimality has been maximizing a posteriori probability (MAP) distribution criterion. Simulated annealing (SA) and iterated conditional modes (ICM) algorithm are two unremarkably used methods for pixel labeling among the existing MAP criterion algorithms. SA can converge to global optimum, but suffers from intensive computation. On the other hand, the results obtained from ICM heavily depend on initialization and hence there is a probability of trapping into local maxima. Hence it suffers from inaccurate estimations. Tseng and Lai [6] have successfully employed hybrid GA-MRF based segmentation, where GA is used to provide better initialization for the ICM algorithm.

In this paper we examine the hybrid GA-GMRF model based segmentation method that takes into account both spatial interaction within each of the bands and interaction between different bands and present a comparison of this method with methods including Genetic algorithm based clustering [3] and GMRF model based segmentation using ICM algorithm [6] for high spatial resolution imagery. The advantages and disadvantages of each method are evaluated by simulations and classification results. Section II reports Genetic algorithm based segmentation and section III, MRF model based segmentation with inter and intra band spatial interaction. Section III describes the hybrid segmentation technique based on GA and MRF with inter and intra band spatial interaction. Results are presented in section IV and section V makes conclusion.

2. Genetic Algorithm Based Clustering

The operations performed in GA based clustering as given by (3) which is considered for comparison is reproduced here for the ease of reference. The number of clusters is known *a priori.*

2.1 Chromosome representation

A chromosome may be encoded with binary, integer or real numbers. We have taken real numbers as the cluster centroid value will be a real number.

2.2 Population initialization

Each string in the population encodes the centers of k clusters. These centers are initialized by random selection from the data set. As an example one chromosome of the initial population (parent generation) is given below:

(51.0, 220.0) (67.0, 54.0) (78.0, 134.0) (98.0, 76.0)

In the example it is assumed that the image has 4 clusters and is with 2 bands. Number of clusters and the number of bands depends on the multi-spectral image being considered.

2.3 Fitness Computation

A function of the ratio of the sum of within cluster separation to between cluster separations which is known as Davies Bouldin's index is used to compute the fitness of a chromosome [3]. The equations are as follows,

The within cluster scatter of cluster k is given by,

$$S_k = \left(\frac{1}{C_k} \sum_{x \in N_k} \| x - z_k \|^2 \right)^{1/2} \tag{1}$$

Where S_k is the average Euclidean distance of vectors in class k, z_k is the centroid of the class k and is computed as $z_k = 1/n_k \sum_{x \in c_i} x$ and n_i is the number of points in cluster C_i.

The distance between cluster C_i and C_j is given by,

$$d_{ij,t} = \left\{ \sum_{s=1}^{p} |z_{is} - z_{js}|^t \right\}^{1/t} \tag{2}$$

Where $d_{ij,t}$ is called the Minkowski distance of order t between the centroids. Here we have considered the distance of order 2.

Then $$R_{i,t} = \max_{j, j \neq i} \left\{ \frac{s_i + s_j}{d_{ij,t}} \right\} \tag{3}$$

is computed to define DB index as,

$$DB = \frac{1}{k} \sum_{i=1}^{k} R_{i,t} \tag{4}$$

The clustering with the minimum DB index gives the properly clustered image.

2.4 Selection

A proportion of existing population is selected to breed a new generation during each successive generation. Roulette wheel selection is employed for selection of individuals.

2.5 Crossover

Single point cross over procedure is carried out by stochastic means with probability µc.
Example:

P1: (51.0, 220.0) (67.0, 54.0) | (78.0, 134.0) (98.0, 76.0)
P2: (65.0, 212.0) (86.0, 25.0) | (133.0, 49.0) (19.0, 26.0)

P1 and P2 represent parent1 and parent2. The line shown is the point where crossover takes place. The genes after that position are exchanged to produce children.

Child1: (51.0, 220.0) (67.0, 54.0) | (133.0, 49.0) (19.0, 26.0)
Child2: (65.0, 212.0) (86.0, 25.0) | (78.0, 134.0) (98.0, 76.0)

2.6 Mutation

The valid genes in the chromosomes are mutated with a probability μ_c

2.7 Termination

The execution is terminated with maximum number of iterations. An elite chromosome preserved in a location outside the population with maximum fitness contains the centers of the final cluster

3. Gaussian Markov Random Field Model

MRF models constitute a powerful tool in image analysis process due to their ability to integrate contextual information associated with the image data [10]. The MRF approach shows the global model of the contextual information by using only local relations among neighbouring pixels. A large category of global contextual models are equivalent to local MRFs. This can be proved by Hammersley-Clifford theorem and thus model complexity is reduced to a great extent. GMRF are a special case of Markov random fields used to model textured images [9].

Let X(i,j) = [x_1(i,j) x_2(i,j) … x_p(i,j)] represent multi-spectral Gaussian random vector of a pixel at location (i,j) in a textured region R. 'p' represents the number of bands in the multi-spectral image. Let μ_1, μ_2,.., μ_p represent mean color intensities in each band. The conditional probability distribution function for MRF, which is assumed to be Gaussian is given by,

$$P\left(X(i,j)\,|\,R|\right)=\frac{1}{\left(\left(2\pi\right)^{P}|\sum|\right)^{1/2}}.$$
$$\exp\left\{\frac{-1}{2}\left[e_1(i,j)e_2(i,j)...e_p(i,j)\right]\ \sum{}^{-1}\left[e_1(i,j)e_2(i,j)...e_p(i,j)\right]\right\} \tag{5}$$

Where [e_1(i,j) e_2(i,j) …. e_p (i,j)] is a zero mean Gaussian noise vector. The spatial interactions of the multi-spectral pixels is given by,

$$e_y\left(i,j\right)=\left(x_y\left(i,j\right)-\mu_y\right)-\sum_{z=1}^{p}\sum_{(m,n)\in N}\alpha_{yz}\left(m,n\right)\left(x\left(i+m,j+n\right)\right) \tag{6}$$

Where μ_y is the mean of the variable x_y(i,j), α_{yz} are model parameters and y takes the values from 1 to p. Subscript N represents different neighbourhood systems. ∑ is the correlation matrix and is given by,

$$\sum=\begin{bmatrix} v_{11} & v_{12} & . & . & v_{1p} \\ v_{21} & v_{22} & . & . & v_{2p} \\ . & & & & . \\ . & & & & . \\ v_{p1} & v_{p2} & . & . & v_{pp} \end{bmatrix} \tag{7}$$

Where v_{kl} is the expected value of e_k e_l and is represented by,

$$v_{kl}=E\left[e_k e_l\right]=\frac{1}{M_R}\sum_{(i,j)\in R}e_k(i,j)e_j(i,j) \tag{8}$$

3.1 Parameter estimation

The spectral vector of a pixel in a multi-spectral image is influenced by its neighbouring pixel vectors. As given by Eq. (5) pixel in each band depends on neighbours of the same band as well as the neighbouring pixels of different bands. Hence the parameters are estimated using pseudo likelihood method adopted in [6], as the product of conditional probability densities of all pixels in region R is not a true likelihood. The product is called the pseudo likelihood function and is given by,

$$\prod_{(i,j)\in R}\frac{1}{\left((2\pi)^{p}\left|\Sigma_R\right|\right)^{1/2}}\exp\left\{\frac{-1}{2}\left[e_1(i,j)e_2(i,j)...e_p(i,j)\right]\Sigma_R^{-1}\left[e_1(i,j)e_2(i,j)...e_p(i,j)\right]^{t}\right\} \tag{9}$$

The parameters can be estimated by maximizing the pseudo likelihood function as given in [6]. As an example let,

$q_1(i,j)=x_1(i,j)-\mu_1$, $q_2(i,j)=x_2(i,j)-\mu_2$,...,
$q_p(i,j)=x_p(i,j)-\mu_p$ *and* $q_{1,mn}(i,j)=x_1(i+m,j+n)-\mu_1$,
$q_{2,mn}(i,j)=x_2(i+m,j+n)-\mu_2$,... , $q_{p,mn}(i,j)=x_p(i+m,j+n)-\mu_p$

Then α parameters for band 1 can be solved using the equation below,

$$\sum_{(i,j)\in R}\begin{bmatrix} q_{1,10}^2 & q_{1,10}q_{1,01} & \cdots & q_{1,10}q_{p,10} & \cdots & \cdots \\ q_{1,01}q_{1,10} & q_{1,01}^2 & \cdots & q_{1,10}q_{p,10} & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ q_{1,mn}q_{1,10} & q_{1,mn}q_{1,01} & \cdots & q_{1,mn}q_{p,10} & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ q_{2,10}q_{1,10} & q_{2,10}q_{1,01} & \cdots & q_{2,10}q_{p,10} & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ q_{p,10}q_{1,10} & q_{p,10}q_{1,01} & \cdots & q_{p,10}^2 & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ q_{p,mn}q_{1,10} & q_{p,mn}q_{1,01} & \cdots & \cdots & \cdots & q_{p,mn}^2 \end{bmatrix}\begin{bmatrix} \alpha_{11}(1,0) \\ \alpha_{11}(0,1) \\ \cdots \\ \alpha_{11}(m,n) \\ \cdots \\ \alpha_{12}(1,0) \\ \cdots \\ \cdots \\ \alpha_{1p}(1,0) \\ \cdots \\ \alpha_{1p}(m,n) \end{bmatrix}=\sum_{(i,j)\in R}\begin{bmatrix} q_1q_{1,10} \\ q_1q_{1,01} \\ \cdots \\ q_1q_{1,mn} \\ \cdots \\ q_1q_{2,10} \\ \cdots \\ \cdots \\ q_1q_{p,10} \\ \cdots \\ q_1q_{p,mn} \end{bmatrix} \tag{10}$$

4. GA–GMRF Hybrid Method

To overcome the drawback of ICM algorithm, which depends on the initialization to produce accurate results, genetic algorithm is employed to give better initialization for ICM algorithm. Using this hybrid method, the fast convergence of ICM and global exploration of GA are achieved simultaneously.

The overall procedure is as follows:

1. A coarse segmentation is performed to get the initial regions using K-means algorithm to reduce the amount of time required in MRF based iterative process and to obtain the mean values.

2. The ICM algorithm initialization using genetic algorithm is performed as follows,

   The spectral vector $X(i,j) = [x_1(i,j)\ x_2(i,j)\ \ldots x_p(i,j)]$ representing the spectral components of a pixel is encoded as an individual. Population of individuals is created, each individual is evaluated and the better individuals are selected to raise the next generation. The procedure is continued till the maximum number of generations is accomplished. For population initialization the result of the K-means algorithm is taken as an individual and the remaining individuals are generated randomly. The function defined in Eq. (5) is used as the fitness function to evaluate each individual. Then the other operations of GA (selection, crossover, mutation) are performed and the individual with the highest fitness is used to give the initial label for ICM algorithm. 100

3. Then the ICM algorithm is performed to produce the final segmented image. The number of generations performed: 100, Population size: 100 and the number of iterations taken by ICM algorithm: 10.

5. Simulation Results

The segmentation results using the GA clustering, ICM and hybrid GA-ICM models for high resolution textured image are presented. Fig. (1) shows a synthetic textured image containing four textures. The size of the image is 200 × 200 pixels. Fig. (2), Fig (3) and Fig. (4) show the segmented images using GA, GMRF-ICM and GA-GMRF-ICM respectively. Pseudo colors are used to indicate the segmented results. We found that segmented results for colored texture image using GA clustering are very noisy because of the reason that it considers only the spectral information without taking into account spatial information. Although MRF model based approach gives better results, because of the initialization problem it suffers from misclassification problem. Hybrid GA-MRF-ICM based approach fully utilizes the features of GA to provide better initialization for ICM algorithm and thus effectively reduces the misclassification problem which is observed in Fig. (4). The convergence plot of the ICM algorithm is shown in Fig. (5).

Figure 1: Original colored texture image

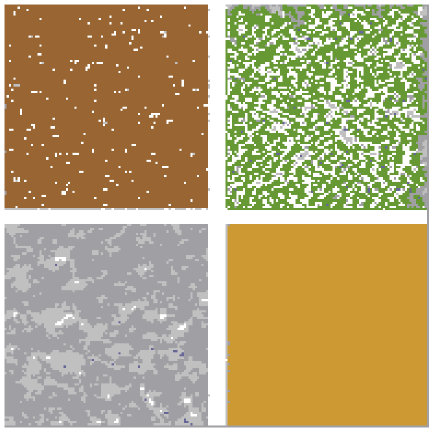

Figure 2: Segmented image using GA clustering

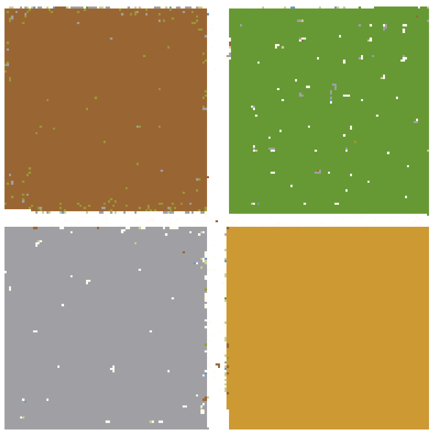

Figure 3: Segmented image using ICM algorithm

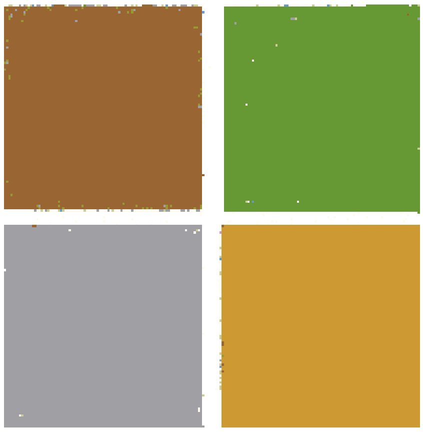

Figure 4: Segmented image using Hybrid GA-ICM algorithm

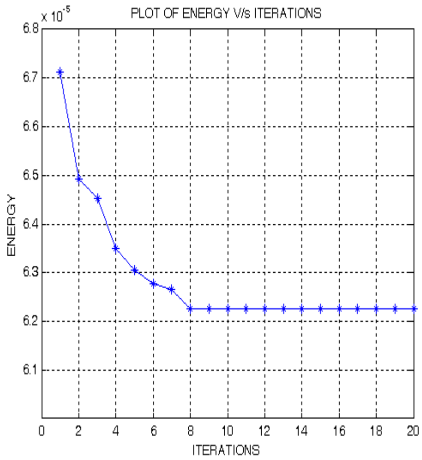

Figure 5: Convergence plot of ICM algorithm

The results of the segmentation can be judged by visual interpretation and the error rate. Because the used images are synthetic images error rate can be easily calculated by the following equation,

$$\frac{\textit{Number of misclassified pixels}}{\textit{Total number of pixels in the image}} x100$$

It is found that, the GA-MRF method has the least error rate compared to other two methods and the error rate of each method is tabulated in the Table 1.

GA based clustering is tested also for medium resolution SPOT image in the multispectral mode having two bands. It is found that GA clustering produces near optimal solutions when the image is non textured as in case of SPOT image. Fig. (6) shows SPOT image of part of the city of Kolkata in the near infrared band. The segmented results are shown in Fig. (7). It can be noted that the GA clustering has yielded optimal results.

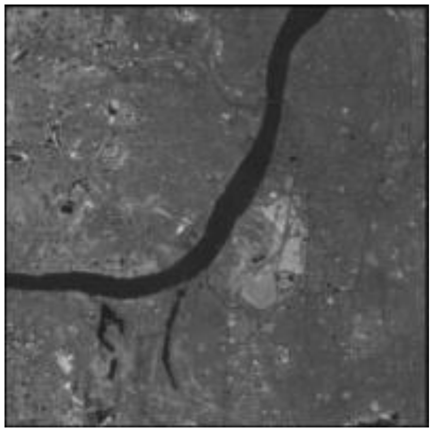

Figure 6: Spot image of Kolkata in near IR band

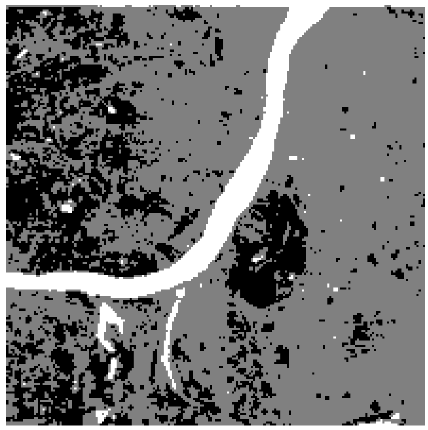

Figure 7: Segmented SPOT image using GA clustering

TABLE 1: ERROR RATE OF SEGMENTATION RESULTS

	Genetic algorithm	GMRF based segmentation	GA-GMRF based Segmentation
Error Rate (%)	More than 40%	11.59	1.2818

6. Discussion and Conclusion:

Comparing the performances obtained with every single algorithm we can conclude that,

- Genetic algoritm based segmentation approach depends only on the spectral information of the pixel without taking into account the spatial information and hence the results are very noisy. The method is optimal only if it is applied to coarse or medium resolution imagery with no noise and cannot be applied for high resolution textured images. Besides the time complexity is also more.

- GMRF model based segmentation using ICM algorithm has the advantage of the computaional cost. Among the segmentation methods considered in this paper, this is the one that has got the lowest computational time. But the disadvantage of this schemata is that the desirable results are not obtained as the ICM algorithm depends heavily on the initial segmentation.

- Hybrid GA-GMRF method generates the best results among all the three methodologies considered in terms of accuracy and time complexity for multispectral textured images. The reason is due to the fact that firstly the model takes into account not only spatial interaction within each of the color bands but also the interaction between the different bands. Secondly it uses GA for the initialization of the ICM algorithm. Hence it has the advantage of combining the fast convergence of ICM and global exploration of GA.

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