MULTI-SPECTRAL SATELLITE IMAGE CLASSIFICATION USING GLOWWORM SWARM OPTIMIZATION

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ABSTRACT

This paper investigates a new Glowworm Swarm Optimization (GSO) clustering algorithm for hierarchical splitting and merging of automatic multi-spectral satellite image classification (land cover mapping problem). Amongst the multiple benefits and uses of remote sensing, one of the most important has been its use in solving the problem of land cover mapping. Image classification forms the core of the solution to the land cover mapping problem. No single classifier can prove to classify all the basic land cover classes of an urban region in a satisfactory manner. In unsupervised classification methods, the automatic generation of clusters to classify a huge database is not exploited to their full potential. The proposed methodology searches for the best possible number of clusters and its center using Glowworm Swarm Optimization (GSO). Using these clusters, we classify by merging based on parametric method (k-means technique). The performance of the proposed unsupervised classification technique is evaluated for Landsat 7 thematic mapper image. Results are evaluated in terms of the classification efficiency – individual, average and overall.

Index Terms— Satellite image classification, Landsat, Hierarchical clustering, Mean shift clustering, Glowworm swarm optimization

1. INTRODUCTION

Land is the basic building block of human civilization. By nature, this precious gift cannot be expanded. To make best use of land and its natural resource, we need good factual knowledge of the land and its features. Accurate knowledge on land-use is very vital for planning and efficient operation. The satellite image is one of the sources which can capture the temporal nature of this knowledge for land utilization. As computer science has raised a stadium where computers are able to perform some "intelligent" tasks, a wide research area has been established in solving the problem of automatic image classification. Land cover mapping information can be used to audit land usage, in the context of city planning and land-usage [1].

For a given satellite image, if there is a lack of ground truth information then unsupervised technique can be applied for automatically classifying a satellite image into distinct land cover regions [2]. In unsupervised technique without prior knowledge of labels, data sets are sub-divided into groups or clusters, based on some attributes. The main aim is to ensure that the distance between intra-cluster is minimum and inter-cluster is maximum. The clustering problems can be developed and analysed hierarchically [3]. Hierarchical clustering constructs a hierarchy of clusters by splitting a large cluster into smaller ones and merging smaller cluster into their nearest centriod [4]. There are two main approaches: (i) The divisive approach, which splits a larger cluster into two or more smaller ones; (ii) The agglomerative approach, which builds a larger cluster by merging two or more smaller clusters.

The hierarchical cluster provides a comprehensive description for any data set. There are many clustering methods to split and merge the data set. They are broadly classified into parametric and non-parametric [3]. In parametric methods prior assumptions are made regarding the shape or number of clusters - K-means clustering [5]. In non-parametric methods no prior assumptions need to be made - Mean Shift Clustering (MSC) [6].

A popular parametric method - K-means clustering, is essentially a function minimization technique, where the objective function is the squared error. Non-parametric technique such as MSC is a procedure for locating the maxima of a mapped function given a set of discrete data points sampled from that function. It is useful for detecting the modes of density given a density function.

In this paper, we present a new nature inspired technique - Glowworm Swarm Optimization (GSO) [7] clustering algorithm for hierarchical splitting and merging of automatic multi-spectral satellite image classification (land cover mapping problem). To compare GSO hierarchical clustering and classification model with Mean Shift Clustering (MSC) we chose Bayesian Information Criterion (BIC), which is most widely used model selection criterion [8]. It depends crucially on the criterion of choosing the non-parametric clustering technique to split the complex large data set into a number of cluster centers by satisfying BIC. Then the cluster centers are used to merge the data set (agglomerative approach) to their respective group. The main challenge here is how best the clusters can be splitted and merged to classify the data set to their respective group. The performance of the hierarchical clustering models – GSO and MSC depends on automatic generation of number of cluster centers to classify efficiently. The performance of clustering is evaluated using classification accuracy - individual, average and overall accuracy. In the proposed model, clustering is analyzed for Landsat TM image from the southern part of India [9].

2. CLUSTER OBJECTIVE FUNCTIONS

The cluster analysis forms the assignment of data set into clusters so that it can be grouped into same cluster based on some similarity measure. Mean Shift Clustering (MSC) [6] and Glowworm Swarm Optimization (GSO) [7] is a non-parametric method for finding cluster centers for a given set of data samples, manifesting an underlying probability density function in *d*-dimensional real space. In contrast to the classic k-means clustering, there are no embedded assumptions on the number of cluster centers (modes). The MSC and GSO technique makes use of kernel functions for detecting the modes of density i.e. locating maxima for a given set of discrete data points. In GSO unlike MSC, proposes to use the collective information available rather than use the individual entropy of the search agents. The most commonly used kernel is the Gaussian or normal kernel which is given by

$$k(x) = c * e^{-x^\wedge 2} \qquad (1)$$

where x is generally the Euclidian distance between two points.

The main idea behind MSC is to treat the points in the *d*-dimensional feature space as a probability density function, where dense regions in the feature space correspond to the local maxima of the underlying distribution. For each data point in the feature space, one performs a gradient ascent procedure on the local estimated density until convergence. The stationary points of this procedure represent the modes of the distribution. Furthermore, the data points associated with the same stationary point are considered members of the same cluster.

The GSO is a population based algorithms to find the multiple optima of multi modal objective functions based on the foraging behavior of glowworms. In GSO algorithm, physical entities (agents or glowworms) are randomly distributed in the search space. Agents are thought of as glowworms that carry a luminescence quality, called luciferin, that emit light proportional to this value. Each glowworm has a variable decision range, bounded at the upper and lower end by the sensor range. Each glowworm is attracted by the brighter glow of other neighboring glowworms. A glowworm identifies another glowworm as a neighbor when it is located within its local-decision domain. Agents in the glowworm algorithm depend only on information available in its own local-decision range to make decisions. For instance, agent having sensor range and different decision domains within search space converges each agent towards available local extrema [7].

3. CLUSTER SPLITTING AND MERGING

In hierarchical clustering, clusters are either merged into larger clusters or split to smaller clusters. It is instructive to see how clustering objective functions change with respect to the change of *K*, the number of clusters. In our study, we combine divisive and agglomerative hierarchical approach. Initially divisive approach is used to estimate number of clusters and its center using non-parametric technique - MSC and GSO algorithm and the agglomerative approach is used to merge the data points using parametric technique (K-means clustering).

MSC is a procedure for locating the maxima of a mapped function given a set of discrete data points sampled from that function. It is useful for detecting the modes of density given a density function. The point moves towards the nearest maxima as determined by the mean shift vector. The mean shift vector always points towards the optima (i.e. gives direction of movement) and the length of the vector is proportional to the distance from the optima. This ensures that points far away from the optima move towards it with bigger steps and slow down as they reach closer. This is the unique point about mean shift has variable gradient ascent.

GSO is loosely based on MSC as it has a component of movement towards the local maxima. It differs in the aspect that it also chooses a component along the neighbour with the highest luciferin value i.e. a neighbour with the present best location. The points that have attained the highest possible luciferin value are not allowed to stagnate; rather they are constantly shifted by an random radius to pick up better cluster centres.

MSC and GSO are iterative procedure and is performed till the system becomes stable. The care has to be taken for splitting the number of clusters by satisfying, Bayesian Information Criterion (BIC) [8].

$$BIC \approx L(\theta) - ½ * k_j * log(n) \qquad (2)$$

where $L(\theta)$ is the log-likelihood measure for the clusters formed; k_j is the number of free parameters for j^{th} cluster; and n is the number of instance for a given data set.

Keeping the modes (cluster centers), k-means clustering is used to group the data point with minimum distance criterion. In agglomerative clustering, the tentative approach is used to merge nearest clusters into one group. This procedure is carried out till specified number of clusters is formed. In our approach, we label cluster centers based on voting method. Thus, data labels aid in labeling the cluster centers. Assignment of label to the cluster centers enables to merge the clusters into their respective group in single step. A simple grouping of similar class labels into single cluster is carried out.

3.1. Performance measures

To classify and evaluate the performance based on individual, average and overall classification accuracy for a given dataset we use hierarchical clustering model – (split the cluster using MSC and GSO, and merge the cluster using k-means). Initially, the dataset is used to arrive at the classification matrix which is of size $n * n$, where n is the number of classes. A typical entry q_{ij} in the classification matrix shows how many samples belonging to class i have been classified into class j. For a perfect classifier, the classification matrix is diagonal. However due to misclassification, we get off-diagonal elements. The individual, average and overall efficiency of class i is defined as for all j.

$$\eta_i = \frac{q_{ii}}{\sum_{j=1}^{n} q_{ji}} \tag{3}$$

$$\eta_a = \frac{1}{n_c}\sum_{i=1}^{n_c}\eta_i \tag{4}$$

$$\eta_o = \frac{1}{N}\sum_{i=1}^{n_c} q_{ii} \tag{5}$$

where q_{ii} is the number of correctly classified samples and n is the number of samples for the class c_i in the data set. The global performance measures are the individual (η_i), average (η_a) and overall (η_o) classification, n_c is the total number of classes and N is the number of samples.

4. RESULTS AND DISCUSSION

In our study, we consider multi-spectral image such as Landsat 7 thematic mapper image acquired from southern region of India. In this work, we are not using 6th band in Landsat data. The portion of Landsat image used is 15 X 15.75 km2 (500 X 525 pixels) and has 30 m spatial resolution. The aim of the study is to develop an unsupervised classifier to distinguish the 9 classes using Landsat 7 original and ground truth image are described in the Figure 1 and Figure 2 respectively. The details of the class and number of pixels are given in Table 1.

Initially, the maximum number of splits generated for Landsat data set by satisfying BIC [8] is 80 cluster centers. The bandwidth in MSC and local decision range in GSO is set by limiting to 80 clusters. To classify by merging to the nearest cluster center is done using k-means technique.

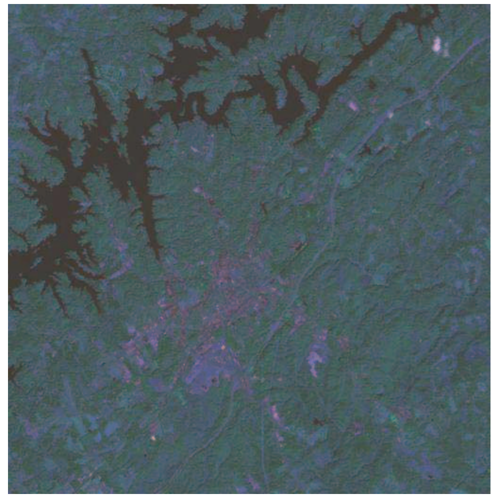

Figure 1: Color composite Landsat image

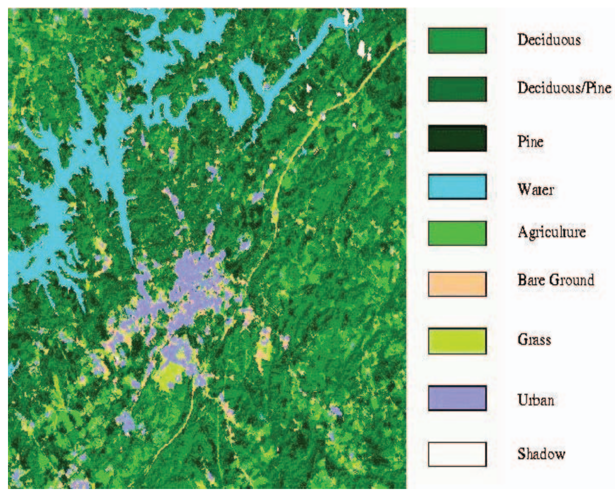

Figure 2: Land sat image ground truth with legend

From Table 2, we can observe that the performance measure of individual efficiency using GSO based hierarchical clustering and classification is better in comparison with that of traditional clustering technique – MSC for Landsat data set. For the samples belonging to C_4 both method has 92.4% individual efficiency. The effect of GSO clustering can be observed, in the individual efficiency of C_6 and C_8 are 71.4% and 78.8% respectively, which is beyond than that obtained in MSC 38.6% and 41.7% respectively. For rest of the classes also GSO outperforms MSC. Also, the result obtained for Landsat data set using the average efficiency has improved from 69.0% to 81.4% i.e. nearly 18% increase. The overall efficiency of the GSO based hierarchical classifier is better in comparison with that of MSC technique. From the performance of classification efficiency we can infer that the GSO is a better clustering technique when compared to MSC.

Class No.	Class Name		Pixels for clustering & classification
	Level-I	Level-II	
C_1		Deciduous	71288
C_2	Forest	Deciduous-Pine	80848
C_3		Pine	24911
C_4	Water		23070
C_5		Agriculture	26986
C_6	Vegetation	Bare Ground	7400
C_7		Grass	12518
C_8		Urban	11636
C_9	Built-up	Shadow	3547
		Total	262144

Table 1. Description of classes and ground truth available

Efficiency individual (η_i)	MSC	GSO
η_1	85.9	87.2
η_2	81	85.6
η_3	69.3	84.1
η_4	92.4	92.4
η_5	76.2	80.2
η_6	38.6	71.4
η_7	69.2	75.7
η_8	41.7	78.8
η_9	66.8	77.5
η_a (efficiency average)	69	81.4
η_o (efficiency overall)	78.1	84.7

Table 2. Performance measure for MSC and GSO in landsat classification

5. CONCLUSION

In this paper, we have presented a new nature inspired technique - GSO algorithm for hierarchical splitting and merging of Landsat data. The Landsat 6 band data are used as inputs to the hierarchical classifier model. The hierarchical technique adopts GSO and MSC for splitting the data set by satisfying BIC and k-means algorithm is used to merge the data set. Overall, the hierarchical classifier model GSO performance is better than the MSC unsupervised technique. The proposed clustering method is feasible for satellite image classification.

6. REFERENCES

[1] David, L., “Hyperspectral Image Data Analysis as a High Dimensional Signal Processing Problem”, *IEEE Signal Processing Magazine*, 19 (1), 17-28, 2002.

[2] Bandyopadhyay, S., Maulik, U., “Genetic clustering for automatic evolution of clusters and application to image classification”, *Pattern Recognition*, 35 (6), 1197–1208, 2002.

[3] Jain, A.K., Dubes, R.C., “Algorithms for clustering data”, *Prentice Hall*, 1988.

[4] Ding, C., He, X., “Cluster merging and splitting in hierarchical clustering algorithms”, *Proc. IEEE ICDM*, 1-8, 2002.

[5] Duda, R., Hart, P., Stork, D., “Pattern Classification”, *Wiley*, 2001.

[6] Fukunaga, K., Hostetler, L., “The estimation of the gradient of a density function, with applications in pattern recognition”, *IEEE Transactions on Information Theory*, 21 (1), 32–40, 1975.

[7] Krishnanand, K.N., Ghose, D., “Theoretical foundations for rendezvous of glowworm-inspired agent swarms at multiple locations”, *Robotics and Autonomous Systems*, 56 (7), 549-569, 2008.

[8] Schwarz, G., “Estimating the dimension of a model”, *The Annals of Statistics*, 6 (2), 461–464, 1978.

[9] Suresh, S., Mani, V., Omkar, S.N., Sundararajan, N., “Multi-spectral satellite image classification using an evolving neural network approach”, *J. Aerosp. Sci. Technol. Aero.Soc. India,* 58 (4), 287-304, 2006.