Embedding Expert Knowledge to Hybrid Bio-Inspired Techniques- An Adaptive Strategy Towards Focussed Land Cover Feature Extraction

Lavika Goel
M.E. (Masters) Student,
Computer Engineering Department,
Delhi Technological University
(Formerly Delhi College of Engg.),
New Delhi,
India.
Email id - goel_lavika@yahoo.co.in

Dr. V.K. Panchal
Add. Director,
Scientist'G',
Defence Terrain & Research Lab,
DRDO, MetCalfe House
New Delhi
India.
vkpans@ieee.org

Dr. Daya Gupta
Head of Department,
Computer Engineering Department,
Delhi Technological University
(Formerly Delhi College of Engg.),
New Delhi,
India.
dgupta@dce.ac.in

Abstract---The findings of recent studies are showing strong evidence to the fact that some aspects of biogeography can be adaptively applied to solve specific problems in science and engineering. This paper presents a hybrid biologically inspired technique called the ACO2/PSO/BBO (Ant Colony Optimization2/ Particle Swarm Optimization / Biogeography Based Optimization) Technique that can be adapted according to the database of expert knowledge for a more focussed satellite image classification. The hybrid classifier explores the adaptive nature of Biogeography Based Optimization technique and therefore is flexible enough to classify a particular land cover feature more efficiently than others based on the 7-band image data and hence can be adapted according to the application. The paper also presents a comparative study of the proposed classifier and the other recent soft computing classifiers such as ACO, Hybrid Particle Swarm Optimization – cAntMiner (PSO-ACO2), Hybrid ACO-BBO Classifier, Fuzzy sets, Rough-Fuzzy Tie up and the Semantic Web Based classifiers with the traditional probabilistic classifiers such as the Minimum Distance to Mean Classifier (MDMC) and the Maximum Likelihood Classifier (MLC). The proposed algorithm has been applied to the 7-band cartoset satellite image of size 472 X 576 of the Alwar area in Rajasthan since it contains a variety of land cover features. The algorithm has been verified on water pixels on which it shows the maximum achievable efficiency i.e. 100%. The accuracy of the results have been checked by obtaining the error matrix and KHAT statistics .The results show that highly accurate land cover features can be extracted effectively when the proposed algorithm is applied to the 7-Band Image , with an overall Kappa coefficient of 0.982.

Keywords:- *Biogeography based Optimization, Rough Set Theory, Remote Sensing, Feature Extraction, ,Particle Swarm Optimization, Ant Colony Optimization, Flexible Classifier, Kappa Coefficient.*

I. INTRODUCTION

Biogeography is a study of geographical distribution of biological organisms. Species keep changing their geographic location, mostly because of disturbance in ecosystem of their habitat (like drought situations, food adversaries, predators, disease etc). This is mostly a group behavior. They move from an unsuitable habitat to another till a suitable habitat is found. Studying this process gives us the way nature optimizes itself. Various engineers and scientists have and are still working on these nature given algorithms. Various concepts of Particle Swarm Optimization [9], Ant Colony Optimization [11], Evolutionary algorithms are working examples of these nature inspired algorithms. Very recently the concept of Biogeography Based Optimization (BBO) has been introduced in this category.

Biogeography is nature's way of distributing species, and is analogous to general problem solutions. In this algorithm, the optimization is done based on migration of species. It uses the well known procedure that nature uses to balance itself. Every node is given intelligence to realize whether the resident place is good for it and option to migrate. BBO algorithm is basically used to find the optimal solution to a problem. But satellite image classification is a clustering problem that requires each class to be extracted as a cluster. The original BBO algorithm does not have the inbuilt property of clustering. To extract features from the image, a modified BBO algorithm is used to make the clusters of different features present in the image [3]. Our proposed Algorithm combines the strengths of this modified BBO technique with the hybrid ACO2/PSO Technique for a more refined image classification. The algorithm is also capable of adapting itself to classify a particular land cover feature better than others based on the expert knowledge.

The organization of the paper is as follows: The paper is divided into 7 sections. S*ection 2* presents a brief review on BBO and hybrid ACO2/PSO Techniques .*Section 3* presents the proposed Framework of the Hybrid ACO2-PSO-BBO Algorithm -the dataset used, proposed architecture, and the parameters used. *Section 4* assesses the accuracy of the Proposed Algorithm by analyzing the KHAT Statistics. *Section 5* presents the classification results of the Alwar Image in Rajasthan using ACO2/PSO/BBO Technique and compares its efficiency with the BBO Technique as well as the traditional probabilistic classifiers. *Section 6* presents the classified images using other recent Soft Computing Techniques and provides a comparison of the Soft Computing Classifiers v/s Probabilistic Classifiers. *Section 7* presents Conclusion & future scope of the proposed work.

II. A BRIEF REVIEW OF BBO AND HYBRID ACO2/PSO TECHNIQUES

A. Biogeography Based Optimization

Biogeography Based Optimization is a population based evolutionary algorithm (EA) motivated by the migration mechanisms of ecosystems. It is based on the mathematics of biogeography. In BBO, problem solutions are represented as islands, and the sharing of features between solutions is represented as emigration and immigration. The idea of BBO was first presented in December 2008 by D. Simon[2]. It is an example of natural process that can be modeled to solve general optimization problems. One characteristic of BBO is that the original population is not discarded after each generation, it is rather modified by migration. Also for each generation, BBO uses the fitness of each solution to determine its emigration and immigration rate [2] [1]. In a way, we can say that BBO is an application of biogeography to EAs. In BBO, each individual is considered as a habitat with a habitat suitability index (HSI) [2] [1], which is similar to the fitness of EAs, to measure the individual. Also, an SIV (suitability index variable) which characterizes he habitability of an island is used. A good solution is analogous to an island with a high HSI, and a poor solution indicates an island with a low HSI. High HSI solutions tend to share their features with low HSI solutions. Low HSI solutions accept a lot of new features from high HSI solutions [1].

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B. Hybrid ACO2/PSO Optimization

The modified hybrid PSO-ACO for extracting Classification rules given by Nicholas and Frietas [6] uses sequential covering approach for rule extraction [10] which directly deals with both the continuous and nominal attribute-values [9].The new version given by Nicholas and Freitas can be understand as follows-

1. Initially RuleSet is empty(_)
2. For Each class of cases Trs = {All training cases}
3. While (Number of uncovered training cases of class A > Maximum uncovered cases per class)
4. Run the PSO/ACO algorithm for finding best nominal rule
5. Run the standard PSO algorithm to add continuous terms to Rule, and return the best discovered rule BestRule
6. Prune the discovered BestRule
7. RuleSet = RuleSet [BestRule]
8. Trs = Trs – {training cases correctly covered by discovered rule}
9. End of while loop
10. End of for lop
11. Order these rules in RuleSet by descending Quality

It is necessary to estimate the quality of every candidate rule (decoded particle). A measure must be used in the training phase in an attempt to estimate how well a rule will perform in the testing phase. Given such a measure it becomes possible to optimize a rule's quality (the fitness function) in the training phase and this is the aim of the PSO/ACO2 algorithm. In PSO/ACO [4] the Quality measure used was Sensitivity * Specificity [4]. Where TP, FN, FP and TN are, respectively, the number of true positives, false negatives, false positives and true negatives associated with the rule [4] [8].

Sensitivity Specificity = TP / (TP + FN) TN / (TN + FP)

Equation 1: Original Quality Measure [7]

Later it is modified as follows-

Sensitivity Precision = TP / (TP + F7) TP / (TP + FP)

Equation 2: Quality Measure on Minority Class [7]

This is also modified with using Laplace correction as;

Precision = 1 + TP / (1+ k + TP + FP)

Equation 3: New Quality Measure on Minority Class [7]

Where 'k' is the number of classes.

So, PSO/ACO1 attempted to optimize both the continuous and nominal attributes present in a rule antecedent at the same time, whereas PSO/ACO2 takes the best nominal rule built by PSO/ACO2 and then

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attempts to add continuous attributes using a standard PSO algorithm.

III. PROPOSED FRAMEWORK FOR THE HYBRID ACO2/PSO/BBO TECHNIQUE FOR LAND COVER FEATURE EXTRACTION

A. Dataset used

Our objective is to use the proposed hybrid algorithm as an efficient Land cover classifier for satellite image. We have taken a multi-spectral, multi resolution and multi-sensor image of size 472 X 576 of Alwar area in Rajasthan. The satellite image for 7different bands is taken. These bands are Red, Green, Near Infra Red (NIR), Middle Infra Red (MIR), Radarsat-1 (RS1), Radarsat-2 (RS2), and Digital Elevation Model (DEM). The ground resolution of these images is 23.5m and is taken from LISS (Linear Imaging Self Scanning Sensor)-III, sensor. The 7-Band Satellite Image of Alwar area in Rajasthan is given in figure 1.

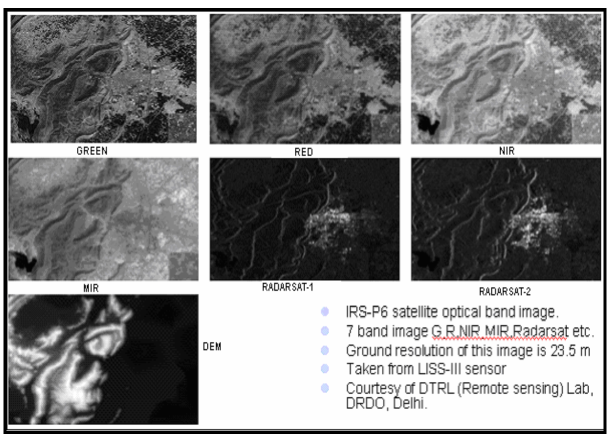

Fig 1. 7-Band Satellite Image of Alwar Area in Rajasthan

B. Defining Parameters for the Biogeography Based Land Cover Feature Extraction Algorithm

The BBO parameters of the Biogeography Based Land Cover Feature Extraction algorithm are defined as follows [3]:

Definition 1: Each of the multi-spectral bands of image represents one Suitability Index Variable (SIV) of the habitat. Thus, SIV€ C is an integer and C € [0,255].

Definition 2: A habitat H € SIV^m where m=7.

Definition 3: Initially there exists a universal habitat that contains all the species to be migrated. Also there are as many other habitats as the number of classes to be found from the image. So the ecosystem H^6 is a group of 6 habitats (one universal habitat and five feature habitats) since 5 features i.e. rocky , barren, water, urban and vegetation are to be extracted from the Alwar Image.

Definition 4: Rough set theory was used to obtain the random clusters of pixels (by using discretization and partitioning concept of rough set theory) and each of the resulting cluster will be considered as mixed species that migrate from one habitat to another. These species can also be termed as 'elementary classes' of a habitat.

Definition 5: Standard deviation of pixels is used as Habitat Suitability Index to help in image classification.

Definition 6: The original BBO algorithm proposed the migration of SIV values from a high HSI habitat to a low HSI habitat. In the above algorithm, rather than moving SIV, the species are moved altogether from a universal habitat to feature habitat. The species do not remain shared: it is removed from the universal habitat and migrated to the feature habitat.

Definition 7: Maximum Immigration rate and Maximum Emigration Rate are same and equal to number of species in the habitat. [2] Maximum species count (Smax) and the maximum migration rates are relative quantities.

Definition 8: Since mutation is not an essential feature of BBO, it is not required in the proposed algorithm. Elitism, too, is an optional parameter; it has not been in the modified BBO Algorithm.

C. Proposed Architecture

The process of Biogeography Based Land Cover Feature Extraction is divided into three steps:

- The first step considers a class and concatenates it with various training sets (i.e. water, vegetation, rocky, barren and urban). These classes and training sets are saved as excel sheets containing x coordinate, y-coordinate, DN values of all the bands. After concatenation each result is stored in a different sheet.

- The next step is to use a Heuristic procedure to decide which land cover property each class belongs to. This is done (in Matlab [13]) by comparing the mean of the Standard Deviation for each of these classes (defined as the Fitness Function) with the Standard Deviation of the Feature Habitat class, using a specific threshold value [3].

- Therefore, Fitness function = difference of the mean of the Standard Deviation for each of these classes. Feature Habitat class = class which contains the standard training set pixels of the 7-Band Image of the Alwar region for comparison.
- In the final step, this function decides which value of mean of standard deviation has minimum difference from the original class.
  i.e.
  HSI = Standard Deviation for each of the classes

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- If this value is within the threshold then that class (species) will migrate to that habitat.[3] If not it can migrate to other class .This can be mathematically represented as below –

Let x_i represent one of the 20 Rosetta [12] classified rough set classes i.e. the universal habitat and y_i training set gray level values i.e. the feature habitat for the i^{th} band of the 7-band image for each of the 5 land cover features to be extracted,

Then,

$$\text{If } \left| \left[\Sigma\sigma_{xi}/n \right]_{UH} - \left[\Sigma\sigma_{yi}/n\right]_{FH} \right|^{6}_{j=1} < \text{threshold},$$

where,

UH=Universal Habitat
FH=Feature Habitat

- then the feature is decided as 'j' i.e. the said Equivalence class corresponds to the feature 'j'.

else

j =1 i.e. it is treated as unclassified .

If it belongs to no class it can simply move to the universal habitat and divides itself to a number of classes which then choose their habitats .The BBO approach can handle a little of inaccuracy in training sets. BBO also takes up inaccurate classes and tune it up for better results.

In this paper we have implemented an integration of Biogeography based land cover feature extraction with the ACO2/PSO technique for features extraction from a satellite image. The proposed architecture of our hybrid algorithm is as follows-

- The image used is the 7-Band Satellite Image of size *472 X 576* of the Alwar Region in Rajasthan. The satellite image is divided into 20 clusters.

- We use rough set theory toolkit i.e. *Rosetta software* [12] for dicretizing each of the 20 clusters using the semi-naïve Algorithm & then partition each of them based on the band which is able to classify the particular feature that we want to extract from the image. Depending on our application, for example, if we want to extract the barren area more efficiently, we choose the green band and for rocky region extraction, we choose the MIR Band. The RS-1 and RS-2 bands are used to extract the urban area and also for extracting the edges of rocky region from the 7-band image. However, the drainages of rocky region are best viewed in the Red band and water and vegetation pixels are best viewed in NIR and MIR Bands. For our illustration, we choose the NIR and MIR band of the 7-band image since we want to extract the water pixels effectively and clearly identify the water body in the image and these are the bands in which the water feature is particularly more highlighted and best viewed. Therefore, we use the NIR and the MIR bands for discretization and partitioning step in the semi – naïve algorithm used for creating rough set equivalence classes, thus creating Equivalence classes for each of the clusters. This is what is termed as Unsupervised Classification .Each of these resultant classes are put in the Universal Habitat.

- Based on the results obtained on applying the BBO algorithm to the 7-Band Image of Alwar region for Land Cover Feature Extraction , we observe that we are able to classify some particular feature's pixels (in our case ,water) with greater efficiency than the other features based on the band chosen & hence, we apply BBO Technique on that particular cluster of the Satellite image of Alwar region since this is the cluster which gives the maximum classification efficiency because it predominantly shows the presence of the feature that is most efficiently classified by the BBO Algorithm.

- We then apply ACO2/PSO Technique [4] on the remainder of the clusters of the image by taking the training set for the 7-Band Alwar image in .arff [4] format as input to generate rules from it using the open source Tool [4] and then applying them on each of the remainder clusters checking for pixel validation for each pixel in the cluster & thus obtain a refined classification of the image .

- Therefore, the working of our proposed hybrid algorithm can be summarized in the form of the following equation and mathematically explained as follows-

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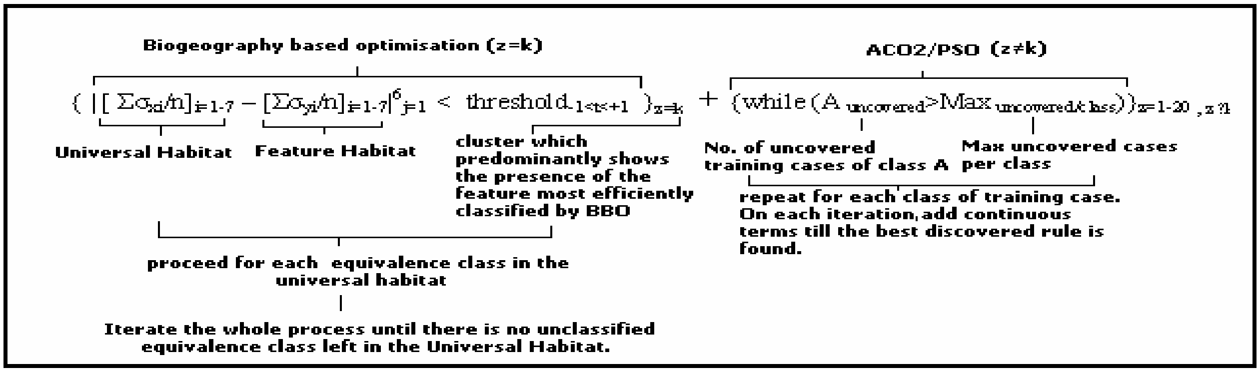

where Universal Habitat contains the rough set classified equivalence classes and the feature habitat consists of the expert generated training set of the original Alwar image in 7-bands.

- Then, for z=k , we proceed in the following manner for the BBO Optimizer -i.e. for each i^{th} band where 'i' ranges from 1-7 , we calculate the difference in the standard deviation of the ith band of the Universal Habitat and the i^{th} band of the Feature Habitat containing the expert generated training set of the image. If this difference is the minimum for the feature 'j' and also less than the pre-specified threshold value of ,-1 < t < +1,then that particular equivalence class is classified as the feature 'j' else j=1(unclassified).The process is repeated for each equivalence class until there is no equivalence class left in the universal habitat and the whole process is iterated till there is no unclassified Equivalence class left.

- For z=1-20, where z ≠ k, we use the ACO2/PSO Optimization, wherein the training set for the 7-Band Alwar image in .arff [4] format is used as input to generate rules from it using the open source Tool [4] for each class of training case and on each iteration, we add continuous terms till the best discovered rule is found. The classification rules are then applied on the remainder of the clusters checking for pixel validation on each of them.

- Hence, we obtain a more refined classified image with an improved Kappa coefficient which is much better than the Kappa Coefficient we get when we apply the original BBO Algorithm on the 7-Band Image.

This in turn leads us to the improved flexible Hybrid version of the BBO Algorithm for Satellite Image Classification which will classify the particular feature chosen by the band used in the unsupervised classification , most efficiently ,which is in turn based on the expert knowledge and the band information contained in the training set of the particular area. Thus, we have efficiently exploited the properties of the BBO technique to adapt itself to a more focussed classification which upon integrating with the ACO2/PSO Technique makes an advanced classifier. Hence, we have obtained a hybrid algorithm which can be adapted to incorporate the expert knowledge for a more flexible, efficient and refined classification. The proposed overall Architecture of this Hybrid ACO2/PSO/BBO Technique is illustrated by means of a flowchart in fig. 2.

IV. ACCURACY ASSESSMENT OF THE PROPOSED ALGORITHM

Accuracy assessment is an important step in the classification process. The goal is to quantitatively determine how effectively pixels were grouped into the correct feature classes in the area under investigation.

Fig. 3 shows the data distribution graph plotted between the average of the Standard Deviations of each land cover feature viz water, urban, rocky, vegetation and barren (plotted on the y-axis) for each of the 7-Bands of the image i.e. Red, Green, NIR, MIR ,RS1, RS2 and DEM (plotted as the x-axis) .From the graph, it can be observed that the minimum difference between the average standard deviations of the NIR and the MIR bands of the Alwar Image is achieved in particularly two land cover features , those of water and urban area ,both of which exhibit the same graph pattern in the NIR and the MIR bands .
i.e.
| average of standard deviation of NIR band ~ average of standard deviation of the MIR band $|_{lowest}$ = {water, urban}

Hence, it can be concluded that these are the two features that will be most efficiently classified by our hybrid algorithm which works in the NIR and MIR bands .
Now we proceed to calculate the classification accuracy of our proposed algorithm using the classification *error matrix.* Error matrices compare, on category-by category basis, the relationship between known reference data

(ground truth) and the corresponding results of an automated classification. We took 150 vegetation pixels, 190 Urban pixels, 200 Rocky pixels, 70 water pixels, 170 barren pixels from the training set and the error matrix obtained is shown in Table II.

The error matrix's interpretation along column suggests how many pixels are classified correctly by algorithm. The diagonal elements (diagonal elements indicate the no. of correctly classified pixels in that category) . From Table I (simple BBO Classifier) , it is evident that the BBO Technique shows the maximum efficiency on the water pixels since it classifies 69 out of 70 pixels correctly as water pixels with only 1 omission error wherein it classifies 1 pixel as rocky one. However, BBO is not an efficient classifier for the urban feature which is also evident from Table II, wherein whole 190 out of 190 pixels were correctly classified as Urban pixels whereas simple BBO Classifier in table I could only classify 88 pixels correctly as urban pixels and it classified 91 pixels wrongly as barren ones. Therefore, we use the Hybrid Technique to classify , in particular the Water and the Urban pixels, with almost 100% efficiency (with no

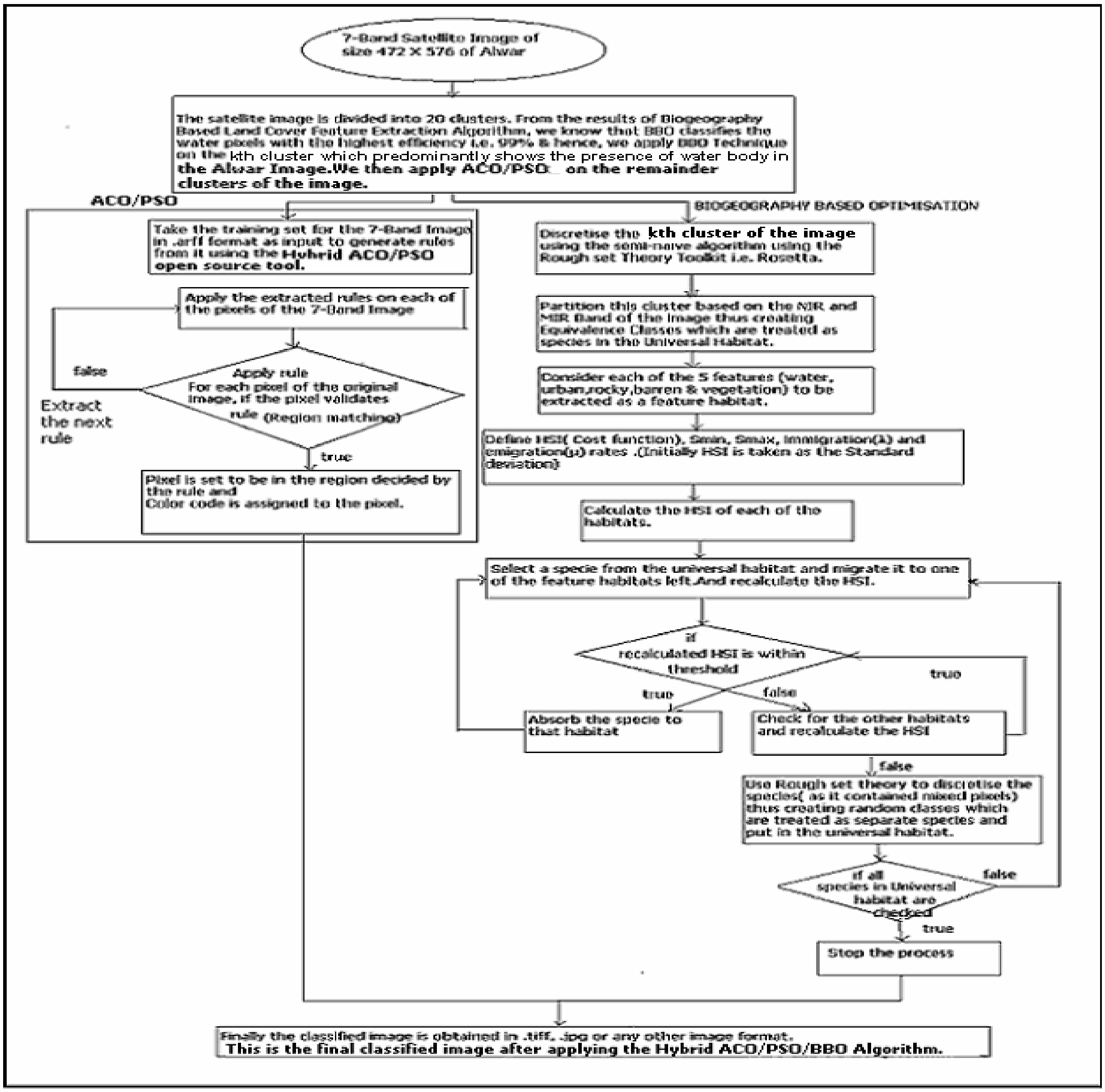

Fig 3.Overall Framework of the hybrid ACO/BBO/PSO Algorithm

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omission errors) ,since for water pixels, we achieve zero omission and commission error (ideal classification) through our algorithm and for urban pixels, a commission error of just 5 in 195 with no omission error (near-ideal classification). This is what was also reflected earlier, from the data distribution graph plotted .
The Kappa coefficient of the Alwar image is calculated using the method described Lillesand and Kiefer. The Kappa (K) coefficient of the Alwar image is 0.9818 which indicates that an observed classification is 98.82% better than one resulting from chance.

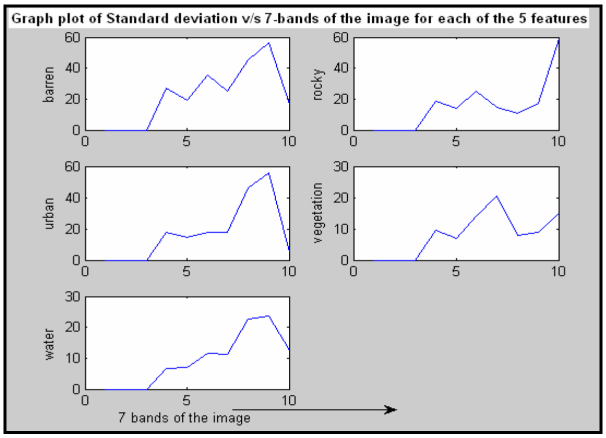

Figure 3. Graph plot of the Standard Deviations of each Land Cover feature v/s each of the 7-Bands in which the Alwar Image is viewed.

Table I. Error matrix when only BBO is applied
Kappa coefficient = 0.6715

	Vegetation	Urban	Rocky	Water	Barren	Total
Vegetation	127	9	0	0	2	138
Urban	0	88	1	0	32	121
Rocky	6	2	176	1	17	202
Water	0	0	3	69	0	72
Barren	17	91	20	0	119	247
Total	150	190	200	70	170	780

Table II. Error Matrix when Hybrid ACO2/PSO-BBO technique is applied.
Kappa Coefficient=0.9818

	Vegetation	Urban	Rocky	Water	Barren	Total
Vegetation	142	0	0	0	0	142
Urban	5	190	0	0	0	195
Rocky	0	0	198	0	3	201
Water	0	0	0	70	0	70
Barren	2	0	1	0	163	166
Total	149	190	199	70	166	774

V. RESULTS AND DISCUSSION

Based on the results obtained on applying the BBO algorithm to the 7-Band Image of Alwar region for Land Cover Feature Extraction, we observe that are able to classify water pixels with the highest efficiency i.e. 99% efficiency and these are the pixels best viewed in the NIR and MIR bands in the BBO Technique & hence, we apply BBO Technique on the 16^{th} cluster of the Satellite image of Alwar region (z=16) since this is the cluster which predominantly shows presence of water body in the Alwar Image . However, BBO shows poor efficiency, in fact the poorest, in classifying the urban pixels as shown in fig. 4. Here the encircled region in the BBO Classified Image shows that BBO wrongly classifies the urban pixels as barren ones which is also reflected from Table I where BBO classifies 91 urban pixels wrongly out of 190 total urban pixels.

Therefore, in order to classify the urban pixels efficiently, we then apply ACO2/PSO Technique [4] on the remainder of the clusters of the image ($z \neq 16$) by taking the training set for the 7-Band Alwar image in .arff [4] format as input to generate rules from it using the open source Tool [4] and then applying them on the remainder of the clusters checking for pixel validation for each pixel in the cluster & thus obtain a more refined classification of the image with an improved Kappa coefficient of 0.9818 which is much better than the Kappa Coefficient of 0.6715 [3] we get, when we apply the original BBO Algorithm on the 7-Band Image . This in turn leads us to the improved Hybrid version of the BBO Algorithm for Satellite Image Classification where both the urban and the water features are classified with the highest efficiency i.e. almost 100% with no omission errors followed by rocky with only 1 omission error (column wise error) and thereafter barren and vegetation features ,respectively. After applying the proposed algorithm to the 7-band of Alwar Image, the classified image is obtained in figure 5. From the figure, it is clearly shown that our proposed ACO2/PSO-BBO classifier is able to correctly classify the encircled region as urban which was wrongly classified by the simple BBO Classifier. The yellow, black, blue, green, red color represents rocky, barren, water, vegetation, urban region respectively. As the threshold limit of HSI matching is lowered, the species do not get absorbed in the feature habitat and return to universal habitat. Those species are further discretized and classified in next iterations (generation).

From the figures 4 & 5, it is evident that the Hybrid ACO2/PSO-BBO Technique produces a more refined image as compared to the BBO classified image. Figure 6 compares the Hybrid ACO2/PSO-BBO Technique with the Minimum Distance Classifier (MDC) & Maximum Likelihood Classifier (MLC). A comparison of the Kappa Coefficients of the Hybrid ACO2/PSO/BBO Classifier with the Traditional Classifiers is given in Table III.

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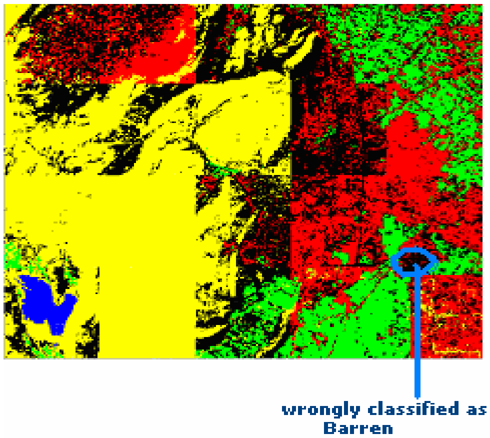


Fig.4. Classified image after applying BBO
(with Kappa Coefficient=0.6715)

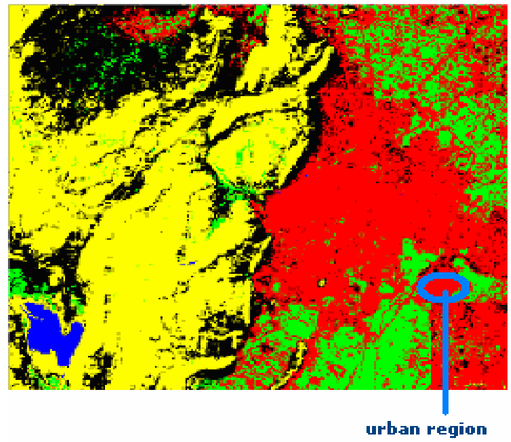
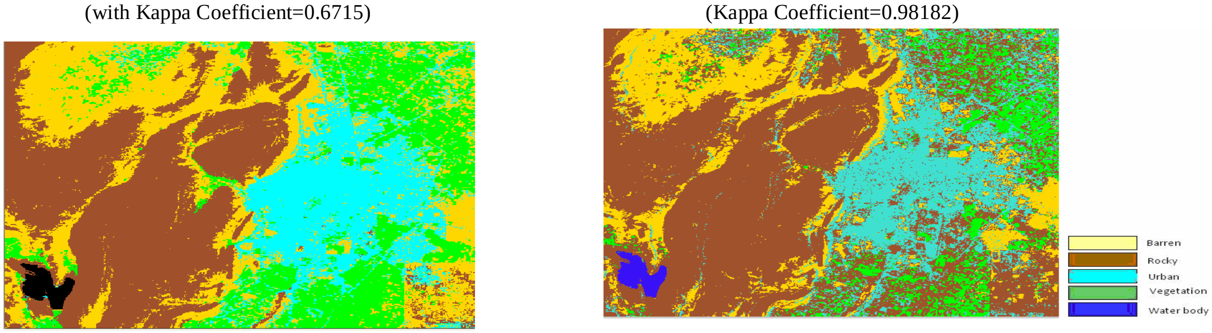


Fig 5. Hybrid ACO2/PSO/BBO Classified Image
(Kappa Coefficient=0.98182)



Minimum Distance Classifier
(Kappa Coefficient=0.7364)

Maximum Likelihood Classifier
(Kappa Coefficient=0.7525)

Fig 6. A comparison with the Traditional Probabilistic Classifiers

Table III. A comparison of Hybrid ACO2/PSO-BBO Classifier with traditional classifiers.

Minimum Distance Classifier(MDC)	Maximum likelihood Classifier(MLC)	Biogeography Based Optimization (BBO)	Hybrid ACO2/PSO-BBO Classifier
0.7364	0.7525	0.6715	0.98182

VI. CLASSIFICATION RESULTS OF OTHER SOFT COMPUTING TECHNIQUES USED FOR SATELLITE IMAGE CLASSIFICATION

From the above discussion, it is evident that the Hybrid ACO2/PSO/BBO Approach is a much efficient classifier as compared to the traditional probabilistic classifiers such as the MDMC and MLC. However, this Hybrid ACO/PSO/-BBO technique also produces comparable results with the image classification results of the other recent soft computing classifiers as shown below. Fig 7(a) shows the Fuzzy Classification of Alwar region which has a Kappa –Coefficient of 0.9134. Fig 7(b) presents the results of an integrated Rough –Fuzzy Tie Up Approach which has a Kappa Coefficient of 0.9700. Fig 7(c) applies the cAntMiner Algorithm on the Alwar Region which has a Kappa Coefficient of 0.964. Fig 7(d) shows the result of applying the hybrid ACO-BBO Technique on the Alwar Image which has a Kappa-Coefficient of 0.96699. Fig 7(e) applies the Hybrid ACO2/PSO Classifier which has a Kappa Coefficient of 0.975. Fig 7(f) presents the results of the Semantic Web Based Classifier on the image with a Kappa Coefficient of 0.9881[5]. The Table IV below compares the Kappa Coefficients of the Soft Computing Classifiers v/s the Traditional Probabilistic Classifiers .From the Table, it is clearly reflected that Soft Computing Classifiers are much more refined & efficient than the Probabilistic Classifiers.

VII. CONCLUSION & FUTURE SCOPE

Discrepant uncertainties inherent in satellite remote sensing images for geospatial features classification can be taken care of by use of soft computing techniques effectively. For the purpose, Rough Sets, Fuzzy Sets, Rough-Fuzzy Tie-up, Ant Colony

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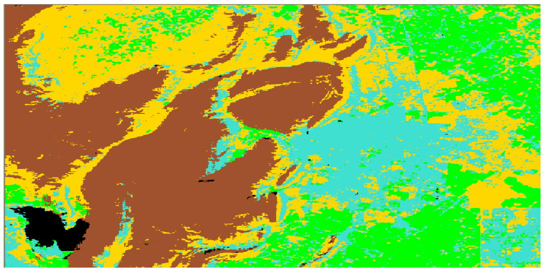
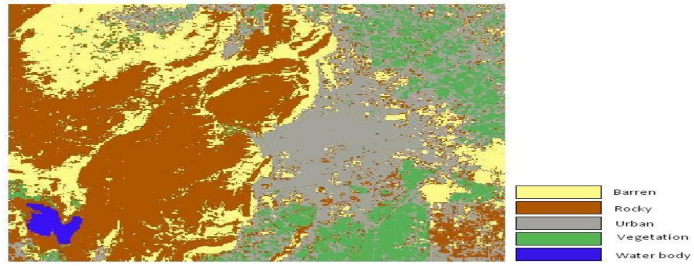
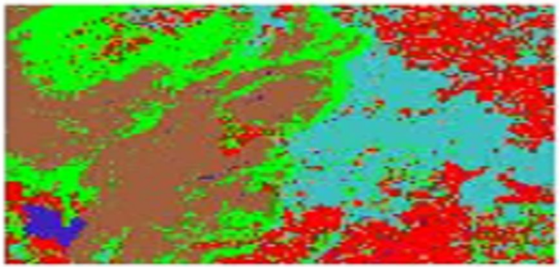


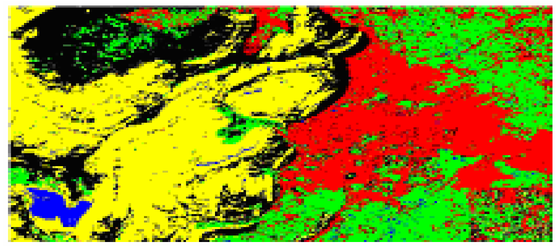
(a) Fuzzy Classification of Alwar Region
(Kappa Coefficient=0.9134)



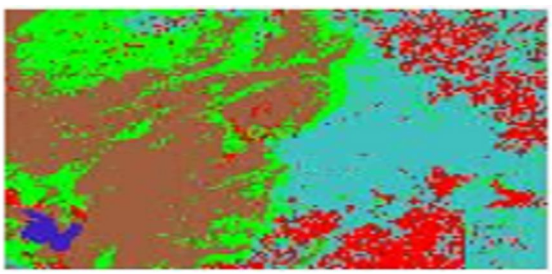
(b) Rough-Fuzzy Tie Up
(Kappa Coefficient=0.9700)



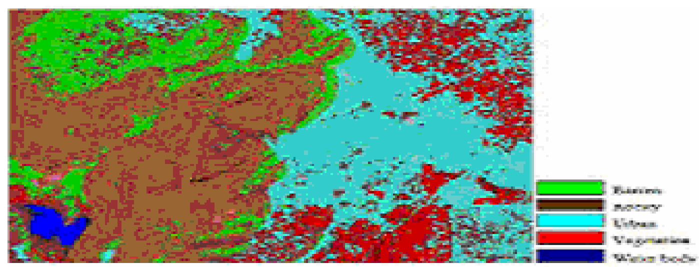
(c) cAntMiner Algorithm
(Kappa Coefficient=0.964)



(d)Hybrid ACO-BBO Algorithm
(Kappa Coefficient=0.96699)



(e) Hybrid ACO2/PSO Algorithm
(Kappa Coefficient-0.975)



(f) Semantic Web Based Classifier
(Kappa Coefficient=0.9881)

Fig 7. Classified Images of Alwar Region after applying various Soft Computing Techniques

Table IV. Kappa Coefficient (k) of Soft Computing Classifiers v/s Probabilistic Classifiers

Minimum Distance Classifier (MDC)	Maximum Likeli-hood Classifier (MLC)	Fuzzy set	Rough-Fuzzy Tie up	cAnt-Miner	Hybrid ACO2/ PSO	Semantic Web Based Classifier	Biogeo-graphy Based Classifier	Hybrid ACO-BBO Classifier	Hybrid ACO2/ PSO/BBO Classifier
0.7364	0.7525	0.9134	0.9700	0.964	0.975	0.9881	0.6715	0.96699	0.98182

(Probabilistic Classifiers) (Soft Computing Classifiers)

Technology Growth

Optimization, Particle Swarm Optimization, semantic web-based classification and Biogeography Based Optimization methods are analyzed in the paper. Semantic-web based image classification is added, as a special instance. Decision system required for any supervised classification can be made consistent and free from indecisive regions by using this spectrum of methods. The Land cover Classification is taken as a case study. It is perceived, from this research, that Kappa coefficient, a well founded metric for assessing the accuracy of classification in remote sensing community, may be used for comparative study of the results from soft computing methods.

This paper presents a novel approach wherein BBO can be combined with ACO/PSO to solve the Image Classification problems in remote sensing for feature extraction from high resolution multi-spectral satellite images .BBO can be used for further refinement of the image classified by simple ACO algorithms such as the cAntMiner Algorithms ,since BBO refines its

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solutions probabilistically after each iteration unlike ACO/PSO which produces new solutions with each iteration and also it is particularly flexible to incorporate the expert knowledge for a more focussed image classification. Hence using a combination of the two techniques i.e. the ACO2/PSO and BBO Technique, can be of major benefit.

In future, the algorithm efficiency can be further improved by lowering the threshold value used in BBO algorithm thus leading to more iterations and refined results. Also, we can further divide the image into more clusters so that a more accurate comparison can be made and the decision about which of the two techniques to be applied on the particular cluster , can be further streamlined. The system performance can be further increased by using better unsupervised classifications and better training sets.

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AUTHORS PROFILE

Lavika Goel has done B-Tech (Hons.) in Computer Science & Engineering & scored 78% marks from UP Technical University, Lucknow (India) in 2008 and currently pursuing Master of Engineering in Computer Technology & Applications from Delhi College of Engineering, New Delhi of India ,batch 2008-2010. She is currently working in Defence Terrain & Research Lab at Defence & Research Development Organisation(DRDO) as a trainee for the completion of her final year project.The work done in this paper is also a part of her M.E. Thesis work.

Dr. V.K. Panchal is Add. Director at Defence Terrain Research Lab, New Delhi. Associate Member of IEEE (Computer Society) and Life Member of Indian Society of Remote Sensing.He has done Ph.D in Artificial Intelligence and is currently working as Scientist 'G' at DRDO,Delhi.Chaired sessions & delivered invited talks at many national & international conferences. Research interest are in synthesis of terrain understanding model based on incomplete information set using bio-inspired intelligence and remote sensing.

Dr. Daya Gupta is the Head of Computer Engineering Department, Delhi College of Engineering, New Delhi. She has done M.Sc. (Maths),Post M.Sc. Diploma (Computers Sc.) from IIT, Delhi, Ph.D. She is a Member of CSI and her specialization is in Computer Software. She has chaired many sessions and delivered invited talks at many national and international conferences.

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