Land Cover Feature Extraction using Hybrid Swarm Intelligence Techniques - A Remote Sensing Perspective

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***Abstract---* The findings of recent studies are showing strong evidence to the fact that some aspects of biogeography can be applied to solve specific problems in science and engineering. The proposed work presents a hybrid biologically inspired technique that can be adapted according to the database of expert knowledge for a more focused satellite image classification. The paper also presents a comparative study of our hybrid intelligent classifier with the other recent Soft Computing Classifiers such as ACO, Hybrid Particle Swarm Optimization-cAntMiner (PSO-ACO2), Fuzzy sets, Rough-Fuzzy Tie up and the Semantic Web Based Classifiers and the traditional probabilistic classifiers such as the Minimum Distance to Mean Classifier (MDMC) and the Maximum Likelihood Classifier (MLC).**

***Index Terms--* Biogeography, Image Classification, Remote Sensing, Ant Colony Optimization , Kappa Coefficient.**

I. INTRODUCTION

In remote sensing the problem of Satellite Image Classification has been solved by using the traditional classical approaches like Parellelopiped Classification, Minimum Distance to Mean Classification, Maximum Likelihood Classification etc. [11]. However, these techniques show limited accuracy in information retrieval and high resolution image is needed. Also these techniques are insensitive to different degrees of variance in the spectral response data.

To provide a solution to the above problems, soft computing techniques were introduced in remote sensing for image classification. Soft computing techniques differ from the above conventional (hard) computing techniques in that, unlike hard computing, they are tolerant of imprecision, uncertainty and partial truth. The principal constituents of soft computing techniques are fuzzy logic [9][10], rough set theory [8][10], neural network theory, probabilistic reasoning, and Swarm Intelligence Techniques [3][6], with the latter subsuming belief networks, genetic algorithms, chaos theory and parts of learning theory. However, the soft computing techniques like the fuzzy classifier [9] [10], and the rough set classifier were not able to provide good result in case of ambiguity sine the main goal of these techniques was to synthesize approximation of concepts from the acquired data [8][10]. Hence, these techniques did not provide very much accurate results with low spatial resolution images. Also these techniques were not able to handle the crisp and continuous data separately.

The solution to the above drawbacks was provided by the recently introduced concept of swarm intelligence [3][6]. Our proposed work bases its fundamentals from Swarm Intelligence. This technique improves the classification of satellite multi-spectral images and is more accurate when working with low spatial resolution images. Our classifier combination provides artificial intelligence to identify the features efficiently classified by BBO and by ACO2 separately based on an analysis of the training set data distribution graph [1][2][5].

II. PROPOSED SOFTWARE ARCHITECTURE FOR OUR HYBRID INTELLIGENT CLASSIFIER

A. Input layer:

A high resolution multi-spectral satellite image is taken as input (in our case 472 X 576 alwar image).

Next the *image is analyzed* by generating its training set and plotting the *data distribution graph* 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, *similarity pattern analysis* is done based on which we observe 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.

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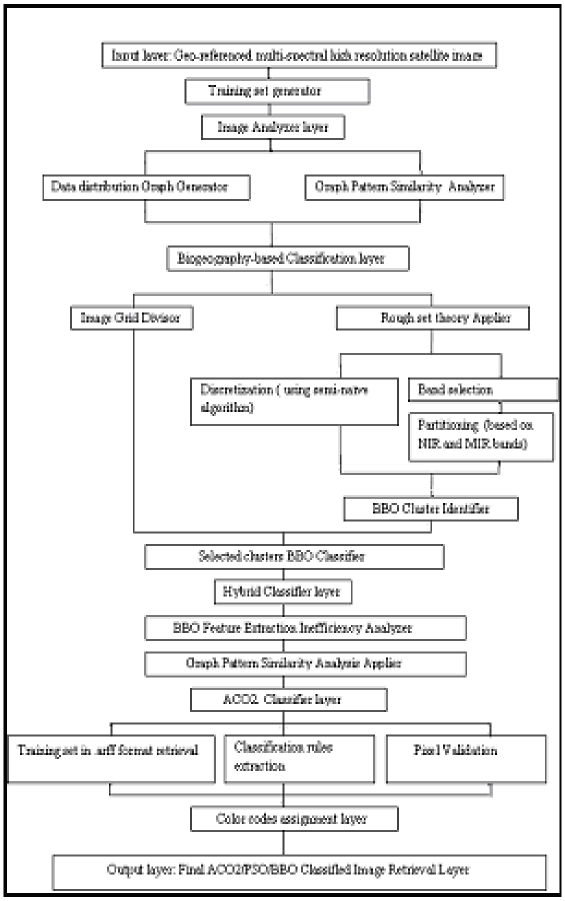

Fig 1. Overall Architecture of our proposed classifier

Based on the observation of the adaptive nature of BBO algorithm for Land Cover Feature Extraction [2] , we observe that BBO is able to classify some particular feature's pixels with greater efficiency than the other features based on the band that we select for creation of equivalence classes in Rosetta [12] . The satellite image is divided into n clusters, in our case n = 20. In the *biogeography based classification layer*, basically we identify to which cluster of the image BBO [1] technique will show good classification efficiency and hence should be applied to. For the purpose, 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. This is because BBO [1] follows an adaptive strategy and will classify the desired feature most efficiently since it has its corresponding *band selected* in the partitioning step. For our illustration, we have chosen the NIR and MIR bands 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.

Rough set equivalence classes are thus created for each of the clusters. This is what is termed as Unsupervised Classification.

Now, we *apply BBO Technique on those clusters* of the satellite image which show the maximum classification efficiency which is due to the fact that these are the clusters which predominantly show the presence of the feature (in our case water) that is most efficiently classified by the BBO Algorithm, let it be the k^{th} cluster.

However, it is also observed that BBO shows a *wide range of efficiencies* in classifying the rest of the features. In other words, BBO is not able to classify all the 5 features with good classification efficiency and shows poor performance on some of the remaining features. In fact, in our illustration, it shows the poorest performance in classifying the urban pixels. Hence we proceed for the ACO2 [5] classification to improve the image classified by BBO. Since, we know from the data distribution graph plotted earlier that our hybrid algorithm will show similar efficiency (i.e. maximum) for the urban pixels too as for the water pixels since their graph pattern in the NIR and MIR bands is similar, therefore, we then apply ACO2 [5] Technique on the rest of the image .In our case, BBO performed better than ACO2 [5] only on the water pixels and hence we applied BBO on the k^{th} cluster. Although BBO gave good performance on vegetation pixels too (since in NIR and MIR bands these are the 2 features that are best viewed) , however, the efficiency was no better than ACO2 [5] classification and hence we did not apply BBO on the vegetation pixels.

In order to apply *ACO2 Classifier* [3] [5], we take the training set for the 7-Band Alwar image in .arff format as input to generate the classification rules from it using the Myra tool and then apply the *extracted classification rules* [7] on each of the remainder clusters of the image. On each of the pixel of the image, we check for *pixel validation* on each pixel in the cluster & thus obtain a refined classification of the image . Finally *color codes are assigned* for each pixel of the image corresponding to the classified feature of each pixel. The color codes for water, urban, vegetation, rocky and barren features are assigned as blue, red, green, yellow and black color respectively.

B.Output Layer:

Final ACO2/BBO Classified image obtained in .jpeg, .tiff or any other image format. The overall software architecture of our proposed intelligent classifier is described in figure 1.

III. MATHEMATICAL FORMULATION OF THE HYBRID CLASSIFIER

Therefore, the working of our proposed hybrid algorithm can be summarized in the form of the following equation in fig 2.

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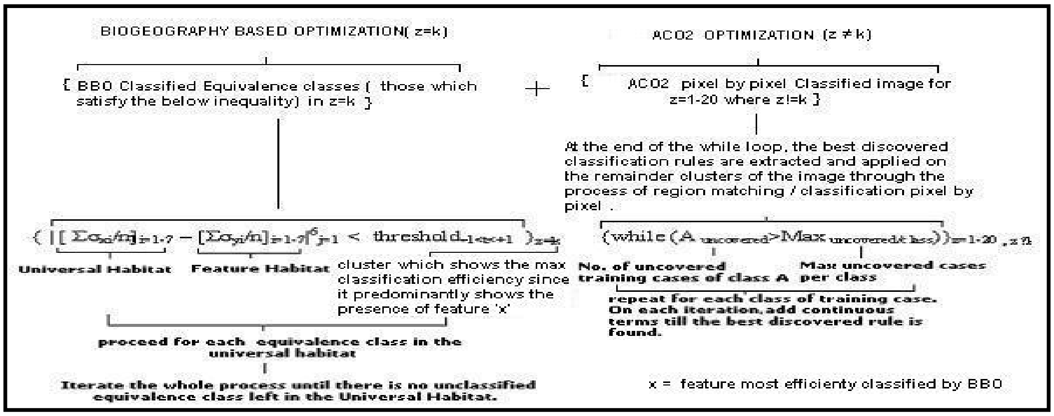
Fig 2.



Mathematical formulation of the ACO2/BBO Algorithm.

IV. PERFORMANCE ANALYSIS RESULTS AND COMPARISON

Table I compares the Kappa Coefficients of our hybrid ACO2/BBO Classifier with the Soft Computing classifiers and the Traditional Probabilistic Classifiers. It is reflected from the table that our proposed classifier is the best amongst all the other recent biologically inspired classifiers namely cAntMiner classifier [5], ACO2/PSO classifier [3] and the most recent BBO Classifier (Kappa Coefficient=0.67)[2] since it has a Kappa Coefficient of 0.97 which is a significant improvement over the simple BBO classifier.

TABLE I.
KAPPA COEFFICIENT (K) OF SOFT COMPUTING CLASSIFIERS V/S PROBABILISTIC CLASSIFIERS

Minimum Distance Classifier(MDC)	Maximum Likelihood Classifier(MLC)	Fuzzy set	Rough-Fuzzy Tie up	cAntMiner	Hybrid ACO2/PSO	Semantic Web Based Classifier	Biogeography Based Classifier	Hybrid ACO-BBO Classifier
0.7364	0.7525	0.9134	0.9700	0.964	0.975	0.9881	0.6715	0.97

(Probabilistic Classifiers) (Soft Computing Classifiers)

V. 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 [8], Fuzzy Sets [9], Rough-Fuzzy Tie-up [10], Ant Colony Optimization (ACO) [5], Particle Swarm Optimization (PSO) [4] and Biogeography Based Optimization [1] (BBO) methods are compared in the paper . Also, semantic-based image classification is added, as a special instance. The Landcover Classification is taken as a case study.

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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