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Swarm intelligence inspired classifiers: A case study with remote sensing perspective

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Abstract: Swarm intelligence inspired classifiers have significant potential for land use/ land cover classification compared to other pattern recognition and classification techniques such as maximum likelihood classification. Land use classifications are always associated with certain amount of uncertainty, vagueness and ambiguity during the classification from the remotely sensed data. In the present paper, optimization techniques like Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) have been applied to perform satellite image classification with fewer amounts of discontinuity, conflicts and constraint of imprecise knowledge and evaluation of data. The proposed work presents a swarm intelligence inspired classifiers for the satellite image classification which provided more precise classifier when compared to others commonly practiced classifiers.

Keywords: Swarm algorithms, Satellite image, Image classification, Matlab

1. Introduction

The Earth's land cover characteristics and its use are key variables in global change. The society today is already in the mainstream of another revolution – the information revolution. This brings enormous changes to life and living, providing new approaches: how to advance the frontiers of previous revolutions particularly those of earth resources mapping and monitoring. Over the last few decades, there has been a significant change on land use and land cover (LULC) across the globe due to the climatic changes and over demand of the growing inhabitants. (Singh et al., 2012).

In remote sensing, satellite based sensors are burgeoning as a major facilitator of geo-spatial information providing different manifestations of the terrain. The satellite image is one of the main sources for capturing the geo-spatial information (Parpinelli et al., 2002). Remote sensing with multi spectral satellite imagery is based on the concept that different features/objects constituting the land cover reflect electro-magnetic radiations over a range of wavelengths in their own characteristic way according to their chemical composition and physical state. A multi-spectral remote sensing system operates in a limited number of bands and measures radiations in series of discrete spectral bands. The spectral response is represented by the discrete digital number (DN). The spectral signature of an object is used for identification much like a fingerprint (Holden and Freitas, 2005).

There are two main type of classifying techniques: supervised and unsupervised classification (Long and Srihann, 2004). When spectral classes, based on numerical information, are grouped first and are then matched by the analyst to information classes, then it is termed as unsupervised classification. Clustering algorithms are used to determine the statistical structures in the data for example K-means approach. In supervised classification, the homogeneous samples of the different surface cover types of interest are used. To recognize spectrally similar areas, numerical information in all spectral bands for the pixels comprising these areas is used. For each pixel in the image a comparison is made with these signatures and is assigned to the class it most closely "resembles". Some of the common supervised classification techniques are parallelepiped, minimum distance to mean and maximum likelihood. The problem faced during the classification of medium spatial resolution imaged such as LISS-III data is poor classification accuracy. Soft computing and advanced tools of image classification were utilized for satellite images are the better option for proper classification of low resolution satellite data with more accuracy (Goel, 2010).

Simultaneously there is a new wide range of computational algorithms that have emerged from the behavior of social insects. Social insects are usually characterized by their self organization with minimum communication or the absence of it. Every social insect individually is self-autonomous. They can obtain information about environment and interact with the remote insects or environment indirectly, by stigmergy. All these features characterize swarm intelligence. The two most widely used swarm intelligence algorithms are Ant Colony Optimisation (ACO) and Particle Swarm Optimisation (PSO) (Kennedy et al., 2001).

In the present paper swarm intelligence algorithms were used for the remote sensing image classification by applying Ant Miner (Rule Extraction Algorithm by ACO); cAnt Miner, Hybrid PSO-ACO and Hybrid PSO-ACO2 algorithm for classification. Ant miner was the first data mining algorithm for the classification based on ACO used (Parpinelli et al., 2002). cAnt Miner was the improved version of Ant

Miner algorithm which can cope with the continuous data also. Unlike a conventional PSO the hybrid PSO-ACO algorithm can directly cope with the nominal attributes, without converting nominal values into numbers in a pre-processing phase. The hybrid PSO-ACO given by Holden and Frietas (2005) uses sequential covering approach for rule extraction. After that they also proposed a new modified version PSO-ACO2 directly deals with both the continuous and nominal attribute-values, a feature that current PSO and ACO rule induction algorithms lack (Fernando et al., 2008) .

Data used: IRS LISS III image (Path 97, row 53) of Feb 14, 2010 was used for the present study. It covers region around Gwalior district, Madhya Pradesh. The training data set consisting of 1486 pixels of the image was collected. Three land cover classes were considered namely, habitation, land and vegetation.

2. Hybrid PSO/ACO algorithm

The Ant Miner and cAnt Miner are very popular approaches for data mining. But an extremely large amount of computation is required with the problem of unusually large amount of attributes and classes. The "standard" binary/discrete PSO algorithm does not deal with categorical values in a natural fashion when compared to ACO (Bratton and Kennedy, 2007). In particular, the standard PSO for coping with binary attributes represents a particle by a bit string, where each binary value such as true or false is encoded as 1 or 0. Sousa et al. (2004) extended the standard binary PSO to cope with multi-valued categorical attributes developing a Discrete PSO (DPSO) algorithm for discovering classification rules.

Holden and Freitas (2005) proposed several modifications to the original PSO/ACO algorithm. It involves the changes in the splitting of the rule discovery process into two separate phases. In the first phase a rule is discovered using nominal attributes only. In the second phase the rule is potentially extended with continuous attributes. This further increases the ability of the PSO/ACO algorithm in treating nominal and continuous attributes in different ways. Both the original PSO/ACO algorithm and the new modified version PSO/ACO2 use a sequential covering approach to discover one classification-rule-at-a-time.

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 optimise a rule's quality (the fitness function) in the training phase and this is the aim of the PSO/ACO2 algorithm. In PSO/ACO the quality measure (QM) used was defined as Sensitivity x Specificity (eq. 1). (Pawlak, 2008).

QM = Quality measure = Sensitivity × Specificity

= TP / (TP + FN) × TN / (TN + FP) (1)

where TP, FN, FP and TN are, respectively, the number of true positives, false negatives, false positives and true negatives associated with the rule. Later it is modified as QM on minority class (eq. 2) and further refined (using Laplace correction) as New QM on minority class as

QM on minority class =
TP / (TP + F7) × TP / (TP + FP) (2)

New QM on minority class = Precision
= 1 + TP / (1+ k + TP + FP) (3)

where k is the number of classes.

So, PSO/ACO1 attempted to optimise 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 attempts to add continuous attributes using a standard PSO algorithm.

```
RS = Φ /* initially, Rule Set is empty */
FOR EACH class C
        TS = {All training examples}
                WHILE (Number of uncovered training examples
                        belonging to class C > MaxUncovExampPerClass)
                Run the PSO/ACO algorithm to discover the
                        best nominal rule predicting class C, called Rule
                Run the standard PSO algorithm to add continuous terms
                        to Rule, and return the best discovered rule BestRule
                Prune BestRule
                RS = RS U BestRule
                TS = TS – {training examples correctly covered by discovered rule}
        END WHILE
END FOR
Order rules in RS by descending Quality
```

Sequential covering approach used by the hybrid PSO/ACO2 algorithm given by Holden and Freitas (2005)

3. Methodology and case study

A flow diagram of the proposed hybrid PSO/ACO algorithm is given in fig. 1 as a flow diagram. In the first step, ACO is used to generate the rules. The process starts by generating rules based on the DNs of training-set data. ACO is an iterative optimization technique. ACO algorithm is guided by the agents' movements in the shared environment locally (Wang et al., 2011). The rules are updated after each iteration.

This is followed by evaluation of the rule generated using the Particle Swarm Optimisation (PSO). The PSO algorithm (Wang et al., 2010) tries to achieve the global maximum of the attribute values through the random interaction between the agents. This process is continued till convergence is achieved.. Thus the final rule was generated. Finally, the rule-set was incorporated using "If – Then – Else" statement in MATLAB. This is called Hybrid PSO/ACO classification algorithm. The pseudo code is given as flow diagram (see fig. 2).

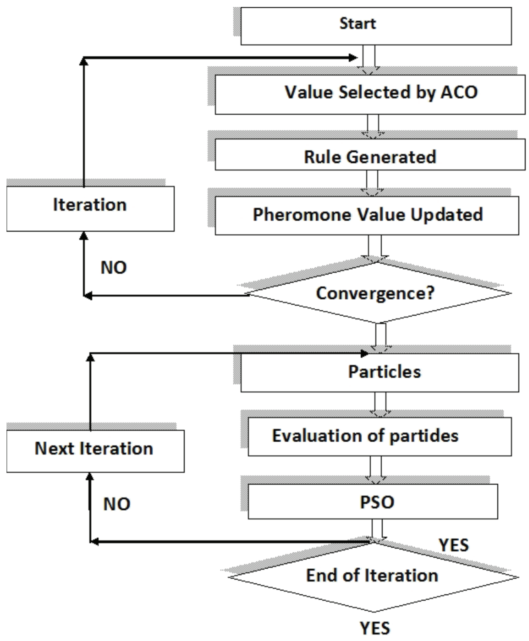

Figure 1: Algorithm applying for Hybrid PSO/ACO classification of LISS III image

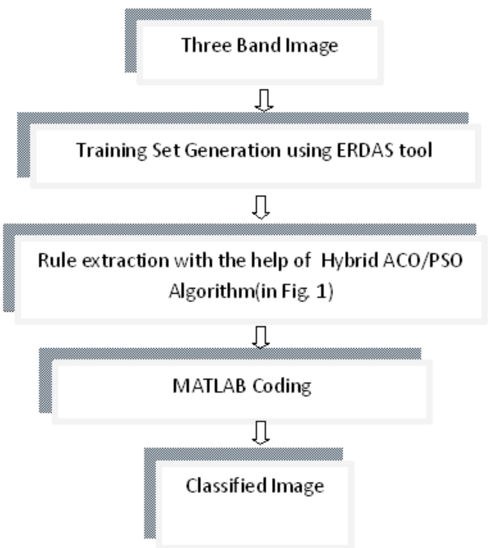

Figure 2: Flow chart for proposed methodology for image classification

The objective of the proposed classification is to use swarm algorithms as an efficient landover classifier for satellite image. Three different bands are taken for classification. These bands are green, red and NIR. They are taken for spectral signatures selection. This training data set was provided by the experts in the form of digital numbers (intensity value pixel in a digital image). These training sets are taken by carefully selecting the areas (pixel by pixel) from all the images and noting the DN values of the pixels.

```
RS = Φ /* initially, Rule Set is empty */
FOR EACH class C
        TS = {All training examples}
                WHILE (Number of uncovered training examples
                        belonging to class C > MaxUncovExampPerClass)
                Run the PSO/ACO algorithm to discover the
                        best nominal rule predicting class C, called Rule
                Run the standard PSO algorithm to add continuous terms
                        to Rule, and return the best discovered rule BestRule
                Prune BestRule
                RS = RS U BestRule
                TS = TS – {training examples correctly covered by discovered rule}
        END WHILE
END FOR
Order rules in RS by descending Quality
```

Sequential covering approach used by the hybrid PSO/ACO2 algorithm given by Nicholas and Freitas

4. Results

In the Hybrid ACO/PSO2, the value of Quality Measures (QM) is inbuilt function in the algorithm. It is based on guiding the pheromone and finding the particle for Global best, to make Global best (i.e. rule to be optimized). Here learning process switches from ACO to PSO on account of Sensitivity and Specificity.

ACO based image classification will automatically reach the optimum level of accuracy. Accuracy assessment on training pixels was based on the kappa coefficient. Kappa values for the other two probabilistic classifiers (i.e. Fuzzy Set Classifier, Rough Set Classifier), cAnt Miner Classifier and swarm classifier are given in table 1. It can be seen that PSO/ ACO2 classifier has the highest level of accuracy (0.975). The images of three bands and classified image are given in fig. 3.

Table 1: Kappa coefficient (k) of various classifiers

Fuzzy Set Classifier	Rough Set Classifier	cAnt Miner Classifier	PSO/ACO2 Classifier
0.785	0.847	0.964	0.975

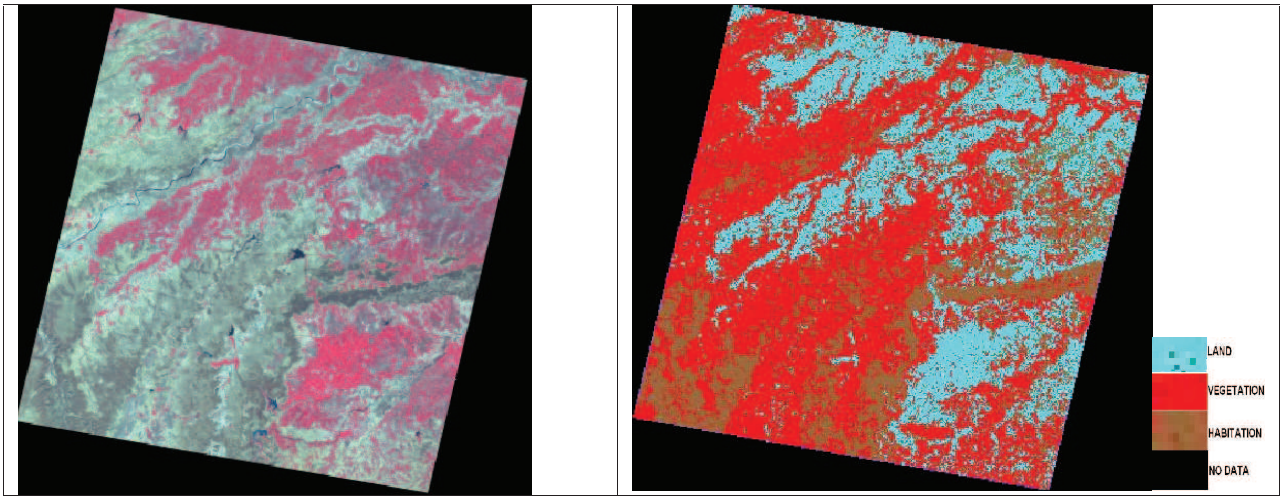

Figure 3: LISS 3 FCC of Gwalior (left) and classified image (right) of the area

5. Conclusion and recommendation

Accuracy of image classification is the one of importagement/ land cover analysis. With the proposed methodologynt factors for analysis of natural resource mana, it is possible to generate LU/LC image with high level of classification accuracy from medium resolution image data. The cAnt Miner ant PSO/ACO2 algorithm for LISS III image (Gwalior region of Madhya Pradesh) gives higher classification accuracy as compared to conventional method and the Fuzzy and Rough set methods.

In results of algorithms PSO/ACO2 inspired from social insect behavior. The results presented are preliminary and there is a considerable scope for improvement to develop these algorithms as efficient classifier. From results it can be seen PSO/ACO2 introduces a great degree of robustness when compared to the other gradient based learning techniques. This paper details the implementation of the improved social insects inspired techniques for satellite image classification. The results show that these techniques are promising for the given problem.Future research will focus on using these algorithms together such that the strengths of this technique can be exploited. The classifiers that perform better for a particular land cover class will be considered more reliable during conflict resolution. So in future these swarm techniques can also be combined with fuzzy-rough approach. Future research will also focus on using multi-spectral multi resolution and multi sensor image fused image for great success.

References

Bratton, D. and J. Kennedy (2007). Defining a standard for particle swarm optimization. Proceedings of the 2007 IEEE Swarm Intelligence Symposium, Honolulu, Hawaii, USA.

Fernando E.B. Otero, Alex A. Freitas, and Colin G. Johnson (2008). *cAnt-Miner*: An ant colony classification algorithm to cope with continuous attributes. Springer-Verlag Berlin, Heidelberg.

Holden, N. and A.A. Freitas (2005). A hybrid particle swarm/ant colony algorithm for the classification of hierarchical biological data. In: Proc. IEEE Swarm Intelligence Symposium (SIS-05), pp. 100-107.

Kennedy, J., R.C. Eberhart and Y. Shi (2001). *Swarm intelligence*. Morgan Kaufmann/Academic Press, San Francisco.

Goel, L. (2010). Land cover feature extraction using hybrid swarm intelligence techniques - A remote sensing perspective. ACEEE Int. J. on Signal & Image Processing, 1(3), pp 14-16.

Long, W. and S. Srihann (2004). Geoscience and Remote Sensing Symposium, Unsupervised and supervised classifications: Land cover classification of SSC image: unsupervised and supervised classification using ERDAS Imagine, IGARSS '04. Proceedings, 4, 20-24.

Parpinelli, R.S., H.S. Lopes and A.A. Freitas (2002). Data mining with an ant colony optimization algorithm. IEEE Trans. on Evolutionary Computation, special issue on Ant Colony algorithms, 6(4), pp 321-332.

Pawlak, Z. (2008). Rough set theory and its applications to data analysis. Cybernetics and Systems 29(7): 661-688.

Singh, P., J.K. Thakur, S. Kumar and U.C. Singh (2012). Assessment of land use/land cover using geospatial techniques in a semi arid region of Madhya Pradesh, India. in: Thakur, J.K., Singh, S.K., Ramanathan, A., Prasad, M.B.K., Gossel, W. (Ed.), Geospatial Techniques for Managing Environmenal Resources. Springer and Capital publication, Heidelberg, Germany, pp. 152-163.

Sousa, T., A. Silva and A. Neves (2004). Particle swarm based data mining algorithms for classification tasks. Parallel Computing 30, pp. 767–783.

Wang, H., H. Xu, S. Yi and Z. Shi (2011). A tree-growth based ant colony algorithm for QoS multicast routing problem. Exp Syst Appl, 38 pp. 11787‑11795.

Wang, H. X. Meng, S. Li and H. Xu (2010). A tree-based particle swarm optimization for multicast routing. Comput Netw, 54 pp, 2775‑2786.