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Hybrid Image Classification using ACO with Fuzzy Logic for Textured and Non-Textured Images

[1] Subba Rao K, [2] Dr. Sambasivarao N [3] Dr. Sammulal P
[1]Associate Professor,[2] Professor, SRITW [3] Assistant Professor, JNTUH

***Abstract:* -- Classification is the process of arranging the pixels into groups, called clusters that have some common characteristics. In this paper a Hybrid, and yet powerful classification method is proposed, which can be used to classify the textured and non-textured images. Traditional classification methods such as statistical classifiers, knowledge-based systems, and neural networks have number of limitations in classifying the images because of strict assumptions, particularly in the presence of the coarse pixels. The Ant Colony Optimization (ACO) is used to generate classification rules from the training set. Due to feedback property of the ACO, it considers all the changes into account in constructing the rules. These rules are then used in the process of classifying test set of the image. An entropy based fuzzy partitioning along with ACO is used to generate rules. ACO enables to construct simple rules to obtain better performance.**

***Index Terms* — Ant Colony Optimization (ACO), Swarm Intelligence (SI), Classification, Textured and Non-Textured Images, Fuzzy Partitioning.**

I. INTRODUCTION

Classification is one of the important activities frequently used in the decision making problems [1]. The process of classification includes giving some label to the objects of interest using predefined classes based on their characteristics. The classification in the image processing is frequently carried out to obtain the land cover information, and to label different regions in the image of interest [2]. Many advanced image classification approaches, such as neural networks, fuzzy sets, expert systems have been used in recent years. These approaches, as shown in Fig. 5, are classified as supervised and unsupervised, or parametric and non-parametric, or hard and soft, or per-pixel, sub pixel and per-field approaches [3]. These approaches are used for classifying both textured and non-textured images. The textured images are characterized by the repeated patterns or elements, which do not contain any shape. The non-textured images are another kind of images where the images contain some shape, but do not contain repeated patterns. The following are the examples for texture and non-textured images.

Fig. 1. Roof Texture Fig. 2. Wall Texture

Fig. 3. Tree Non-Texture

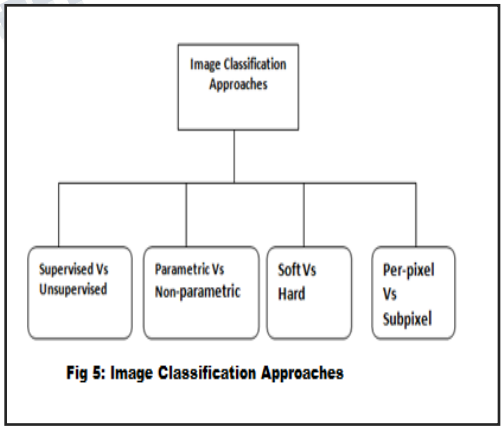

Fig 5: Image Classification Approaches

The supervised classification methods have sufficient referential data that is used as training sample. The Maximum likelihood, and Minimum distance, Artificial Neural Network, Decision Tree are the example for the supervised approaches [4].In the case of unsupervised approaches; no predefined classes are used to classify the images. The classes are obtained through analysis, by labeling and merging the spectral classes into meaningful

classes. ISODATA, K-means clustering are the examples for the unsupervised approaches.

In the parametric approaches the parameters are obtained from the training samples. Maximum likelihood and linear disciminant analysis are the examples this kind. In non-parametric approaches no assumptions and statics are made about the data. Artificial Neural networks, decision tree, expert systems are the examples for the non-parametric approaches.

In hard classification approaches, each pixel is allocated to single class, causing large errors, when estimating with coarse spectral data. Maximum likelihood, decision tree, and Artificial Neural networks are the examples of this kind. In soft classification approaches, a measure of similarity for every pixel is computed with some heuristic function [8], which will be almost same for the same class of pixels. It provides more information and accurate result, even in the presence of coarse spectral data. The fuzzy sets and fuzzy logic are the examples of this kind. The soft classification minimizes errors due to the mixed or coarse pixels problems using the fuzzy logic. In per-pixel classification, the signature is computed from training samples for given feature. This signature contains all the information of the training samples, but ignores the affect of the mixed pixels. MLH, minimum distance, ANN DT are the examples of this kind. To address the problem of the per-pixels approaches, subpixel approaches have been developed, that provide better representation and accurate estimation even in the presence of the mixed or coarse data in the image. The fuzzy expert system is an example for this kind. In this paper a hybrid classification method which is derived from both fuzzy logic and a nature inspired optimization technique [11] called Ant Colony Optimization expert system is proposed to improve the performance of the classification for both textured and non-textured images. The nature inspired optimization techniques have their source of inspiration in nature. The algorithms are developed from the behavior of the biological components of nature.

The rest of the paper is organized as follow: Section 2 presents the related work on rules generation procedure. Section 3 presents the working of ACO algorithm. Section 4 presents the conclusions. Section 5 presents the list of references.

II. ANT COLONY OPTIMIZATION

The advancement in the swarm intelligence methods and techniques has created lot of scope for solving complex classification problems. One of the swarm intelligence techniques called, Ant Intelligence has solved many complex classification problems efficiently ranging from traveling salesman, data clustering, networking, data mining and image classification [1]-[2]. The Ant Colony Optimization is derived from the natural behavior of the biological systems of the ants. It was first proposed by Colorni et al. in 1991 [6]. This is an unsupervised technique, and does not use any parameters during the classification. A powerful and efficient classification technique is designed by combining subpixel approach with the soft classification approach, which is also called as hybrid classification technique. The natural ants behavior, is just simulated in the form of an algorithm to find the optimal solution by considering the local heuristic, distributed computing and knowledge from the past experience. There are two main characteristics of the ACO. First, Indirect communication by the ants laying down a chemical substance called pheromone in their paths. This pheromone attracts other ants to follow their path. Second, is the positive feedback that enables fast discovery of the optimal solution.

Ants follow the path that has largest amount of pheromone. One unique characteristic of the pheromone is that it evaporates over time. The paths that have large amount of the pheromone attract more number of ants causing a shortest path is being created. The paths that have less amount of pheromone tend to evaporate over time and thus considered to be the longest paths. This method has proven to be efficient and produced satisfactory result in solving complex problem [8]. Parpinelli et al. proposed ACO for generating the rules using the system called Ant-Miner [9]. Ant-Miner produces better accuracy and simple rules than that of decision tree methods. The simple rules can be generated. The ACO has number of advantages. First, it is a distribution free. Second, it is rule generation algorithm, and uses simple equations than complex equations. Finally, it needs minimum knowledge of the problem domain.

III. WORKING OF ACO

In this section, a classification rules generation algorithm based on Ant Colony Optimization, called Ant-

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Miner is used [10]. This section is organized into five subsections, namely, discretization of continuous gray values, Ant-Miner Description, rules construction, rule pruning, and using the rules for classification

i. Discretization of Continuous Gray Values

It is a preprocessing step for converting the RGB images into gray scale images which contain the continuous values ranging from 0 to 255. Discretization is one of the effective techniques in dealing with continuous values in the process of rule generation. The fuzzy set theory is used to discretize continues values into discrete values like (0-14), (15-21), (22-37) and so on. This process reduces the number of rules and improves the efficiency of the ACO classification.

ii. Rule Mining Description

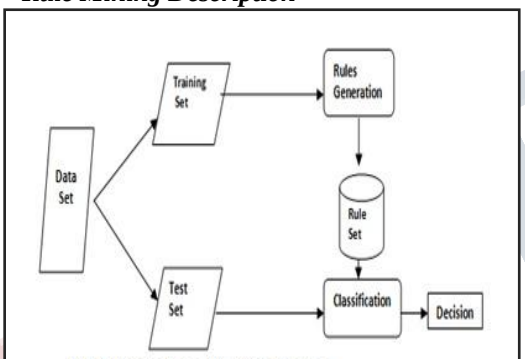

Fig 6: Image Classification Process

The process of rules generation is analogous to the collective process of the ants seeking for the food. Ant-Miner uses the step-by-step procedure to generate rules that classify all training set of pixels or almost all training set [1]. Each classification rule has the form: If rule_antecedent then rule_consequent, where rule_antecedent is the conjunction of the terms. The rule_consequent is the prediction of the class. A term is triple that contains <attribute, operator ,and value>. An attribute is corresponding to the brightness value. The operator element is always is "=". The value element is a value in the domain of the attribute. For example, gray=12. The rule may contain one or more terms along with consequent to which these rules are mapped. The rules are will be in the following form:

IF<term1 AND term2 AND term3> THEN---- c1
ELSE IF<term4 AND term5> THEN ----------c2
ELSE IF<term6 AND term7 THEN ----------c3
ELSE <term 9 AND term 10} THEN----------c4

Where c1, c2, c3 and c4 are called classes. Training Samples (TS)={ a1,a2,a3, a4,a5, a6,a7,a8,a9}, where a1, a2, and so on a9 are the attributes, and the subsets {a1,a2,a3}, {a4,a5}, and {a6,a7,a8},{a9,a10} are corresponding to the classes c1, c2, c3 and c4 respectively.

Rules Construction Process

The construction is an iterative process through the rules are extracted.. The rules set initially set to empty, a set of ordered rules are generated through the iterative process. The entire data belonging to the pixels is divided into two sets: Training Set and Test Set as shown in the Fig 6. The rules are extracted from the Training Set using the ACO algorithm with fuzzy logic. The best rule that covers a subset of the training set is found and is added to the Rule Set The training samples are covered by best rule removed from the training set. And remaining pixels in the training set are classified with next ordered rule, if and only if previous rules not able to classify.

Table 1: Pheromone Matrix

F/N	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
1	1	1	1	1	1	1	1	1
:	1	1	1	1	1	1	1	1
n	1	1	1	1	1	1	1	1

The feature set is fi={ 1,2,3,…….n}. The pheromone at every node must be updated. The Pheromone matrix is represented as follows. 〖 τ〗_i^j=1 ------(1)
[for all i=1 to n and j=1 to 8] where each cell contains the pheromone value, which is updated every time a new ant calculates the pheromone. It is also called Confusion Matrix. The heuristic Information can be calculated using

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the following equation. Where F is for Feature and N is for neighbor.

$$\eta_{j}^{i}=\left(\sum_{k=1}^{m}\left[\left(\bar{X}_{i}^{k}-\left(X_{i}\right)\right)\right]\right)/\left(\sum_{k=1}^{m}\left[\square\left(1/\left(N_{i}^{k}-1\right)\right)\sum_{j=1}^{N_{i}^{k}}\left(\left(X_{ij}^{k}-\bar{X}_{i}\right)\right)\right]\right) \text{----(2)}$$

Where m- is the number of classes, xi – is the feature subset of the feature set fi , xki - is the feature subset in fi in the class k, xij - jth element in the xi of fi in the class k. The probability can be calculated from the equations (1) and (2) of the conditional termij, to include it to the current rule or not. It is clear from the above equation that the heuristic information is obtained from the ratio of the discrimination between classes and discrimination with in the class. The probability that an ant(t) can select the current term to include it in the rule is determined by:

$$P_{i}^{j}(t)=\left(\left[\tau_{i}^{j}(t)\right]\eta_{j}^{i}\right)/\left(\sum_{i}^{j}\left[\tau_{i}^{j}(t)\,\eta_{j}^{i}\right]\right) \text{------(3)}$$

The correctness of the rule can be validated using the equation as bellow:

$$\text{Quality}=(TP/(TP+FN))\cdot(TN/(FP+TN)) \text{---(4)}$$

Where TP =True Positives, correctly predicted by the rule

TN=True Negatives, total number of negatives cases wrongly predicted

FP=False Positives, total number of positive cases wrongly predicted

FN=False Negatives, total number of negatives wrongly predicted by the rule. If the value of the

Quality is large, and then it indicates the rule is higher quality.

Rule Pruning

The objective of the rule pruning is to remove unnecessary terms and rules that contribute less in classification. This has three advantages: First, a shorter rule can be easily understood by the user than long rule. Second, it improves the predictive accuracy of the rules. Third, it also prevents the data from over fitting the training data [12]. The process is repeated until there exist a single term or the rule quality is no longer improved.

Using the Rules for classification

The entire data related to the pixels is split into two parts called Training Set and Test Set as shown in Fig.6. The Training Set is used to generate the classification rules. These classification rules are then applied on the Test Set. If the Test Set contains N number of instances in which C instances are correctly classified, then the predictive accuracy of the classifier is calculated using equation as bellow:

$$\text{accuracy}=C(\text{Correctly\_Predicted})/N(\text{Total\_Number\_of\_Instances}) \text{ -(5)}$$

Updating the Pheromone

Initially pheromone of all the terms is set according to the equation (3). Once if the rule is accepted, the pheromone levels of all the terms that involve in the rule is increased, otherwise decreased. The rate of decrement is determined by the evaporation factor e. At each term the amount of pheromone is computed as:

$$\tau_{i}^{j}(t+1)=\tau_{i}^{j}(t)+\Delta\tau_{i}^{j}(t) \text{-------(6)}$$

$$\Delta\tau_{i}^{j}(t)=1/|S_{i}^{j}|\sum_{(S\in S_{i}^{j})}f(S) \text{ ---------(7)}$$

$$f(S)=((\text{Recals}+\text{Precisions}))/N_{feat} \text{ -----(8)}$$

where Sij –is the number of solutions generated at 't' iteration, s – solutions feature set. f(s) –is called fitness function, Nfeat - is the number of features in the solution set s.

CONCLUSION

The hybrid classification methods can improve the performance of the overall classification system. The textured and non-textured images can be classified using the Hybrid method which will minimize the errors due to the mixed or coarse pixels problems and coarse spectral data. This can be further extends to non-textured image classification and analysis.

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REFERENCES

[1] David Martens and Manu De Backer, "Classification With Ant Colony Optimization," IEEE Trans on Evolutionary Computing, Oct 2007, pp. 651-665.

[2] Xiaoping Liu and Xia Li, "An Innovative Method to Classify Remote Sensing Images Using Ant Colony Optimization," IEEE Trans. on Geosciences, Dec 2008, vol. 46, no. 12, pp. 4198-4208.

[3] D.LU and Q. WENG, "A survey of image classification methods and techniques," International Journal of Remote Sensing, March 2007,pp. 823-870.

[4] Jia Li and James Ze Wang, "Classification Of Textured And Non-Textured Images Using Region Segmentation," Proc. 7th Int. Conf. on Image Processing, 2000.

[5] T. Chattoopadhyay, B. Bhowmic and A. Sinha, "Application of image processing in industries," CSI Communication, July 2012, pp. 8-11.

[6] A. Colorni, M Dorigo et al. "Distributed Optimization by Ant Colonies," in Proc. 1st Eur. Conf. Artif. life, 1991, pp. 134-142.

[7] Kwang Mong Sim and Weng Hong Sun, "Multiple ant colony optimization for network routing," 1st Int.Symp Cyber Worlds, 2002 pp.277-281.

[8] R S Parpinelli, H S Lopes And A A Freitas, " An ant colony algorithm for classification rule discovery," in Data Mining: A Heuristic Approach, H.A. Abbas, R.A. Sarker, and C.S Newton, Eds, London, UK.: Idea Group Publishing, 2002.

[9] R S Parpinelli, H S Lopes And A A Freitas, "Data Mining with Ant Colony Optimization" IEEE Tran. Evol. Comput. vol. 6, no.4, pp321-332, Aug 2002.

[10] H. B. Duan, "Ant Colony Algorithms: Theory and Applications," Beijing, China: Science Press, 2005.

[11] Manish Dixit et.al. "An Exhaustive Survey on Nature Inspired Optimization Algorithms", in International Journal of Software Engineering and Its Applications Vol. 9, No. 4 (2015), pp. 91-104

Subba Rao K, pursuing Ph.D in Computer Science and Engineering from JNTUH, Hyderabad, in the area of Digital Image Processing.

Dr. N. Sambasivarao, received his Ph.D degree in Software Engineering, from Anna University, India. His research areas are Digital Image Processing, Software Engineering, Data Mining, and Mobile Computing.

Dr. P. Sammulal, received his Ph.D degree in Parallel Computing from JNTUH, India. His research areas are Digital Image Processing, Network Security, Mobile Computing, and Parallel Computing.