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Rules Generation by Ant Colony Optimization for Classifying Textured and Non-Textured Images

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Abstract—The classification rules are the means through which different parts of the image can be classified. In this paper a novel, and yet powerful rules generation 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. The Ant Colony Optimization (ACO), which is a kind of swarm intelligence, is used to generate classification rules. 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 the image. An entropy based fuzzy partitioning is used to partition the gray level domain into the number of classes, which are used in the process of the rules generation using the Ant Colony Optimization. Simpler rules are constructed 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. 1, 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 one kind of images, which do not contain any shape, but the some patterns are repeated. The non-textured images are another kind of images where the images contain some shape.

The supervised classification methods have sufficient referential data that is used as training sample. Maximum likelihood, 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 discriminant analysis are the examples of parametric approaches. In non-parametric approaches no assumptions are made about the data. These do not use statistical parameter for obtaining the class information. 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. This may produce large errors, when estimating with coarse spectral data. Most classifiers, such as maximum likelihood, decision tree, artificial neural networks are the examples of this kind. In soft classification approaches, a measure of similarity for every pixel is defined with some heuristic function, which will be almost same for the same class of pixels. It provides more information and accurate result, even with coarse spectral data. The fuzzy sets and fuzzy logic are the examples of this kind. The soft classification minimizes errors due to the mixed pixel problems using the fuzzy logic. In per-pixel classification, the signature is computed from the spectra of all the training samples with respect to a given feature. This signature contains all the information of the training samples, but ignores the affect of the mixed pixels. Maximum likelihood, minimum distance, artificial neural network, decision tree 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 derived from both fuzzy logic and Ant Colony Optimization expert system is proposed to improve the performance of the classification for both textured and non-textured images.

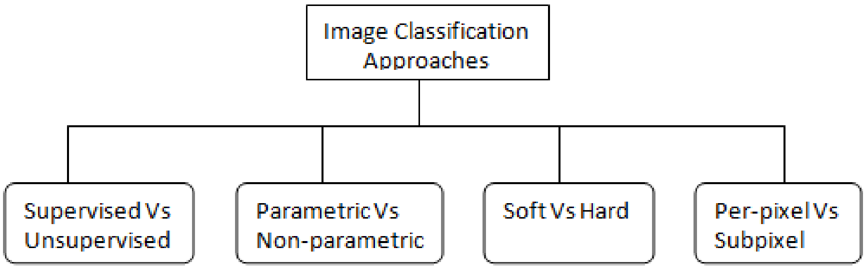

Fig. 1. Image Classification Approaches

II. THE CLASSIFICATION PROCESS

For any image, classification process contains several steps to come up with some decision. The major steps of this process are illustrated in Fig. 2. The image acquisition, image processing, feature extraction and decision making [5]. The image is acquired using any of the image acquisition devices such as camera, scanner, and mobile. Once the image is acquired it is processed to remove the noise present in it. The processed image is now given as input to the feature extraction module to extract the feature of the interest. These features are nothing but the non-overlapping characteristics of the image. Using these features, a decision is made using the machine or the human designed methods that contain the specific information of the image. The result contains the desired information of the image.

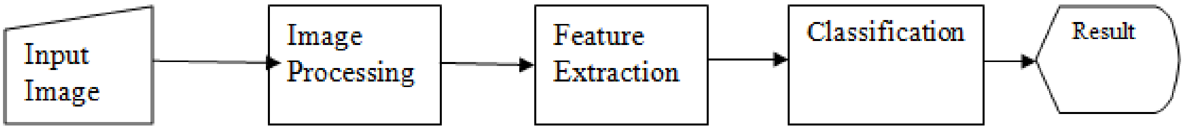

Fig. 2. Classification Process

III. 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. This uses subpixel approach to overcome mixed pixel problems. A powerful and efficient classification method 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 shortest path between given source and destination. It finds 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. Another characteristic is the positive feedback that enables fast discovery of the optimal solutions.

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, which does not need training data to follow predefined normal distribution. Second, it is rule generation algorithm, and uses simple equations than complex equations. Finally, it needs minimum knowledge of the problem domain.

IV. WORKING OF ACO

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

Ant-Miner uses the discretized data for rules generation. 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 AND term8> 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.

iii. Rules Construction

The Ant-miner algorithm is applied on the discretized gray level values for effectively generating the classification rules. The rules set initially set to empty, a set of ordered rules are generated through the iterative process. The best rule that covers a subset of the training set is found. This best rule is then added to the list of the discovered rules. The training samples are covered by best rule removed from the training set. And remaining training set are classified with next ordered rule, if and only if previous rules not able to classify.

The process of selecting the term plays vital role in this entire process of the classification. A heuristic function is designed so that the computation time can be greatly reduced, than random selection. The heuristic value for each term will be almost same for the training samples that fall under one class. A heuristic function based on frequency of the data is used [9], where the heuristic value η_{ij} of the term t_{ij} is defined as:

T_{ij} = n umber of training samples that fit to the conditional term term$_{ij}$

$\sum_n$ =total number of samples

$freqT_{ij}^{w}$ = frequency of the class in T_{ij} --------------------------(1)

$$\eta_{ij} = \frac{\max\left(\sum_n freqT_{ij}^1, \sum_n freqT_{ij}^2, \sum_n freqT_{ij}^3, \ldots, \sum_n freqT_{ij}^k\right)}{\sum_n freqT_{ij}} ----(2)$$

this newly computed heuristic value is used in calculating the probability of the "term$_{ij}$" along with pheromone amount. The amount of the pheromone is computed as follow [1]:

$$ap_{ij}(t=0) = \frac{1}{\sum_{i=1}^{A} bi} --------(3)$$

where ap_{ij} is the amount of pheromone for the conditional term$_{ij}$, and t is the current ant, A is the sum of attributes, it can be obtained using the number of rows and cols in the image. For example number of rows and cols are 5 and 6 respectively then, A is equal to the product of rows and cols, that is 12. And here the bi is any value of the attributes.

The equations (2) and (3) are used to calculate the probability of the conditional term$_{ij}$, to include it to the current rule or not. The probability is calculated as follow:

$$P_{ij}(t) = \frac{\eta_{ij}(t).ap_{ij}(t)}{\sum_{i=1}^{a}\sum_{j=1}^{b}\eta_{ij}(t).ap_{ij}(t)} --------(4)$$

It is clear that the probability of the term can be included depends on both frequency and amount of pheromone.
The correctness of the rule can be validated using the equation as bellow [12]:

$$Quality = \left(\frac{TP}{TP+FN}\right).\left(\frac{TN}{FP+TN}\right) ----(5)$$

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, then it indicates the rule is higher quality.

iv. 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.

v. Using the Rules for classification

The entire data related to the pixels is split into two parts called Training Set and Test Set. 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:

$$accuracy = \frac{C(correctly\_predicted)}{N(Total\_numberof\_instances)} - - - - - (6)$$

vi. 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, the pheromone in decreased for the terms that do not involve the rule as well. The rate of decrement is determined by the evaporation factor e. At each term the amount of pheromone is computed as:

$$ap_{ij}(t+1) = (1-e).ap_{ij}(t) + \left(\frac{Quality}{1+Qality}\right).ap_{ij}(t) - - - (7)$$

where e is the pheromone evaporation coefficient, and Quality is the Quality of the classification rule.

V. 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 methods which will minimize the errors due to the mixed pixel problems and coarse spectral data. Hence the textured and non-textured images can be efficiently classified using the rules generated Ant colony Optimization and Fuzzy Logic.

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