A Novel Hybrid Image Analysis using ACO and Fuzzy Logic for Textured and Non-Textured Images

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Abstract

Image analysis is the process of extracting quantitative and useful content from images by means of image processing approaches. In Image analysis, the classification process plays vital role in arranging the pixels into groups, called clusters that are similar in characteristics. In this paper a novel hybrid image classification method is proposed, which is used to analyze both textured and non-textured images. The image classification generally makes an attempt to group all the pixels that are strongly related to the objects in the image of interest. Classification rules are extracted from the input image using the unsupervised swarm intelligence technique called ant colony optimization (ACO), which are then used to group pixels. These classification rules are obtained from the training set of the image and further pruning process is applied to eliminate those rules that contribute less in the classification process on the test set of the image. Fuzzy partitioning technique along with ACO is used to generate simple rules to produce better results.

Keywords

Ant Colony Optimization (ACO), Swarm Intelligence (SI), Classification, Textured and Non-textured Images, Fuzzy Partitioning.

I. INTRODUCTION

Image analysis generally is the step followed by the image segmentation which is also called image classification. The classification step attempts to group the pixels of the input image that are related in some way. This step requires the classification rules to make the pixels into groups. The rule generation step is an important in the entire classification process. If the rules are simple and accurate they produce better classification results, which then simplifies the job of the image analysis. These are number of classification methods such as rule induction method, decision tree, neural networks, fuzzy sets, and expert systems [1]. These classification techniques are further categorized into four different categories such as shown in the Fig.1 below.

The supervised classification methods need predefined referential data in advance as training samples to classify. Maximum Likelihood (MLH), Minimum Distance (MD), Artificial Neural Network (ANN), and Decision Tree (DT) are of this kind [2]. In the case of unsupervised techniques, predefined data are not needed to classify. The classes are trained using an iteration process and analysis, by labeling and merging pixels into meaningful classes. K-Means (KM) clustering is an example this kind.

Parametric techniques train parameters out of training samples, which are then used as means for classification. Linear Discriminate Analysis (LDA) and Maximum Likelihood (MLH) are examples of this kind. Whereas, non-parametric techniques put no assumptions and statistics are trained for parametric data. Expert Systems (ES), Decision Tree (DT), and Artificial Neural Networks (ANN) are examples of this kind.

Soft classification techniques use a heuristic function to produce the heuristic value, which is almost same for the same class of pixels. This is appropriate in the presence of coarse spectral data to reduce the misclassification errors. The Fuzzy Sets (FS) is an example of this kind. Hard classification techniques label each pixel to a single class which causes more inaccuracy in this context. This uses artificial neural networks (ANN) and decision tree (DT) for classifying.

Per-pixel categorization techniques generate a signature by computing for a given characteristic from training samples, but fails about mixed pixels. This uses minimum distance (MD), artificial neural networks (ANN) and decision tree (DT) for this kind. To tackle the issues of the Per-pixel classification techniques, sub pixel classification techniques have come into existence to yield better classification results in this context [3]. This uses fuzzy expert system (FES) for this purpose.

In this paper a hybrid image analysis method, which has been defined from the characteristics of both fuzzy expert system and ant colony optimization that is a kind of swarm intelligence technique is proposed. This method has been used to analyze textured images for extracting the regions or objects in them and also non-textured. In the rest of this paper Fuzzy Partitioning with ACO which is used to extract the classification rules is explained. The Rule pruning for eliminating rules that contribute less in determining the object is explained. The experimental results are discussed from the Caltech 101[4] image dataset.

II. FUZZY PARTITIONING WITH ACO

The nature inspired optimization algorithms [5] have enabled lot of scope for the complex optimization problems. The complex problems have several factors such as number of variables, time complexity and space complexity etc, to affect the result. The particle swarm optimization, bee colony optimization, genetic algorithms [6] and ant colony optimization are some of nature inspired optimization algorithms. The ant colony optimization (ACO) algorithm has given solutions to many difficult problems such as traveling salesman, data clustering, finding the

shortest path in network, data mining, and finally image processing. The ACO methodology has been modeled from the nature inspired activities of the natural ants which was first proposed by Colomni in 1991 [7]. This works as rules induction or extraction algorithm. This algorithm is used to derive the rules for analyzing the image for extracting the individual parts or objects from it. The image can be textured which contains the repeated patterns, but does not contain any shape and non-textured images which in turn contain some shape. The algorithm works as shown in the following Fig 2:

- i. Read input image and convert it into gray scale image
- ii. Divide the image into training and test sets
- iii. Extract the classification rules on training set by means of aco and fuzzy logic
- iv. Use these rules to test for accuracy of the rules on the test set
- v. Prune rules that are not desirable
- vi. Use these rules now to classify and analysis the entire image for identifying the different regions of interest in the same image.

Fig 2. Image Analysis Algorithm

The input image is divided into two sets: training and test. The classification rules are trained from training set using the ACO [8]. A heuristic value for each and every pixel is calculated, which will be nearly identical for the same class of pixels. Heuristic value of a pixel at ant for the training set is calculated from the following equation:

$$\eta_{ij}^i = \frac{\sum_{k=1}^m (\bar{x}_i^k - \bar{x}_l)}{\sum_{k=1}^m \left[\frac{1}{N_i^k - 1} \sum_{j=1}^{N_i^k} ((x_{ij}^k - \bar{x}_i)) \right]} \quad \text{--- (1)}$$

Where, m denotes number of classes, x_i denotes training set, $\bar{x}_i$ is the mean of the training set, x_i^k denotes subset of training set under the class k. x_{ij} denotes j^{th} element in the class k. It is understandable that from the above equation(1) heuristic value is calculated as a ratio between of the discrimination of classes and within the class. Initially number of classes are extracted using the 2^k rule [9]. The probability that an ant(t) can choose the current term to put it in the rule is directed by following equation:

$$P_i^j(t) = \frac{[\tau_i^j(t)] \eta_j^i}{\sum_i^j \tau_i^j(t) \eta_j^i} \quad \text{--- (2)}$$

Where, τ_i^j is the value in the confusion matrix which is constructed from the heuristic values through a repetitive process. This confusion matrix is updated as the pheromone value of the pixel is changing about an ant every time as shown in the Table 1.

Table 1 Confusion matrix

Gray Level /Heuristic Range	H1-Hi	Hi+1-Hk	Hk+1-Hm
1	C1	C2	C3
:	C4	C5	C6
N	C7	C8	C9

A term is a triple that has attribute, operator, and value. An attribute characterizes the brightness value. Operator can be ">=" or "<=" . Value denotes a any meaningful value under domain of attribute. The range for the attribute value about brightness is defined between 0 and 255. The triple term is expressed as gray=27. The rule contains one or more terms that results a consequent for which it is mapped. The list of rules are specified in the following structure:

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if (A(i,j)>=0 && A(i,j)<=w) .....c1
elseif(A(i,j)>w && A(i,j)<=2*w) .....c2
elseif(A(i,j)>2*w && A(i,j)<=3*w).....c3
elseif(A(i,j)>3*w && A(i,j)<=4*w).....c4
elseif(A(i,j)>4*w && A(i,j)<=5*w) .....c5
elseif(A(i,j)>5*w && A(i,j)<=6*w) .....c6
elseif(A(i,j)>6*w && A(i,j)<=7*w) .....c7
elseif(A(i,j)>7*w && A(i,j)<=8*w) .....c8
elseif(A(i,j)>8*w && A(i,j)<=9*w) .....c9
else (A(i,j)>14*w && A(i,j)<=15*w) .....c10

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Where c1,c2,c3..c10 are classes.

III. RULES EXTRACTION AND PRUNING

The rules extraction starts with dividing the image data into two parts called training and test sets. The rules are extracted from the training set by conducting the repeated process with ants. These extracted rules are then applied on test set to validate and prune the rules obtained. All the extracted rules may not be useful in analyzing the image. The rules that contribute less are pruned to make the rules simple and efficient.

The rule pruning process is applied on the rules obtained during the training phase, only those rules that lead to incorrect classification on the test set are discarded. These rules are removed from the rule list for further obtaining the fewer rules which is also called refined rule list. These rules are then used to analyze the entire image for extracting the objects or regions of interest. The I-Prune technique [10] is used to prune the rules. Those item rules that are interested are retained and not interested are rejected or removed from the rules.

The correctness of the rule is calculated from the precision [11] and recall in the following manner:

$$\text{Quality} = \left(\frac{\text{TP}}{\text{TP} + \text{FN}} \right) \cdot \left(\frac{\text{TN}}{\text{TN} + \text{FP}} \right) \text{-----}(3)$$

Where TP denotes number of pixels truly estimated (True Positives) by the rule. TN denotes total number of negatives pixels estimated (True Negatives). FP denotes number of pixels that are wrongly estimated as Positives (False Positives). FN denotes number of pixels that are wrongly estimated as Negatives (False Negatives) by the rule. The large quality value results in higher quality rule. Accuracy is used to measure how close the calculated value is to

the original value, and the precision is used to estimate how close the calculated values are with one other.

IV. EXPERIMENTAL RESULTS

In this paper Caltech 101 image data set is used. Some of the textured images and non textured image are used for testing and extracting the object and regions of interest. The image “brain_0066.jpg” of size 300x258 is used, which is non-textured image to extract the region of interest. The image “image_0026.jpg” under the category of Dalmatian which is of type textured is used to extract the different regions in the image. These images are used in the Matlab for processing and analyzing the regions of interest. The images are first converted into gray scale and features are extracted and used by the ACO to derive rules.

Fig 3. Brain tumor extraction

Fig 4. Image_0026 analysis

V. CONCLUSION

The proposed hybrid image analysis method has analyzed the images for its internal objects or regions with more accuracy. The textured and non-textured images from Caltech 101 have been tested and analyzed using this method. This has given higher accuracy for internal objects and regions of interest for the given input images of both categories. This method can be further used to group similar type of images into corresponding group.

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