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Object- based Image Classification using Ant Colony Optimization and Fuzzy Logic

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Abstract*: Image analysis enables to get meaningful information from a digital image by applying the image processing techniques. During the process of extracting of this meaningful information number of challenges needs to be addressed for a high-resolution image. These high-resolution images which contain minimum of 300 pixels per inch are also known as 'coarse' images. One common problem of coarse image is it combines the spectral properties of intermixed pixels. This nature of coarse image will lead to ambiguity in grouping the pixels into clusters which are in turn constitute to different objects in the input image. To reduce this ambiguity in classifying or grouping the pixels, Ant Colony Optimization and Fuzzy Logic which is a Hybrid classification technique is proposed. The ACO has solved many classification problems. In this paper ACO and Fuzzy based to group the pixels into meaningful groups for coarse image and results are compared with various other unsupervised classification methods such as ISODATA and K-means

Keywords*: Classification, ACO, Fuzzy Logic, Object-based Image Analysis, Coarse image

I. INTRODUCTION

Image analysis has become very important thing in many applications. This is particularly useful to understand the environment changes, medical images, remote sensing images to get land cover information, to get in touch with wildlife, knowing the climate condition of the place to which people cannot visit. This is also useful in security and disaster management. Image analysis is performed generally after image segmentation [1]. In the images segmentation pixels that are similar in some way are grouped into clusters which can form some objects. There are various classification methods such as neural networks, decision tree, expert systems, fuzzy sets and object-based classification to group similar pixels [2]. In the context of the coarse image which is a high-resolution image, it can combine different spectral properties of land cover information.

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For example, a high-resolution image which spans 1km^2 in a forest area, the image contains typically forest, but also contains open patches, roads, trees, water resources, rocks and fens etc. [3]. Even if the details of the image appear to be forest, but it is not completely forest. It contains different things or objects, but the forest vegetation dominates all these things, hence appear to be forest.

The intermixed pixels in the image will affect the classification process to group the pixels into meaningful objects. These intermixed pixels will impose some confusion or ambiguity in the process of grouping. To address this problem of ambiguity Ant colony optimization [4] with fuzzy logic is used which has already addressed same kind of problems in many applications. The process of image analysis will exploit the meaningful and quantitative information from the image. This step always will be followed by the image segmentation process which in turn uses different classification methods based on the problem. The image segmentation process will give building blocks to the image analysis. Image segmentation process is carried out on two basic properties of pixels: *discontinuity* and *similarity*. In discontinuity-based image segmentation, image is segmented based on the sudden changes in intensity values. In the context of similarity-based approach image is segmented into its constituent objects or parts by grouping the pixels that are similar in some way. These segmentation methods can be classified into 4 categories: a) point-based b) edge-based c) region-based d) combined [5].

The process of forming pixels into groups that are *similar* and contribute to represent some shape and size is called "*Object based classification*". The outcome of this process is again an image that contains objects each of which contains homogeneous pixels by forming pixels into clusters or groups. The objects produced in this process will represent different features in the image and hence are more significant. This process also enables to classify objects depending on texture, shape and context. The problem in classifying pixels is, some pixels that are on the border appear to be belong to both regions divided by the border. It is very critical to make decision about such pixels that lie on the border. Taking the advantage of the ant colony optimization the entire problem of classifying the pixels that are at border and intermixed becomes simple. In the process of classification for each pixels a heuristic value is computed [6] which is almost same for same class or group of pixels. With this the job of classifying pixels that impose some sort of confusion will be easy.

The remainder of this paper is organized as follows: section II gives the background work, section III gives a list of issues in Object-based image analysis, section IV explains the working proposed methodology of ACO with fuzzy logic and section V presents results analysis and VI gives Conclusion.

II. BACKGROUND WORK

A. Image Segmentation

The main objective of the image segmentation is, it produces non-overlapping object or regions. In the segmentation process two things are very important: pixels that are relatively homogeneous and pixels that are relatively semantic [5]. In the process of segmentation, the pixels that are relatively homogeneous are grouped into one group. The pixels that are semantically related are also grouped to form into another group. These groups are known as '*objects Candidates'*. These need to be converted into meaningful objects further to understand and extract the meaningful and quantitative information from the image. The outcome of the segmentation process are the building blocks which are in turn used for the image analysis process for extracting the meaningful information. These segments which are also known regions. These regions have different additional spectral information such as mean, median, minimum, maximum values, variance etc.

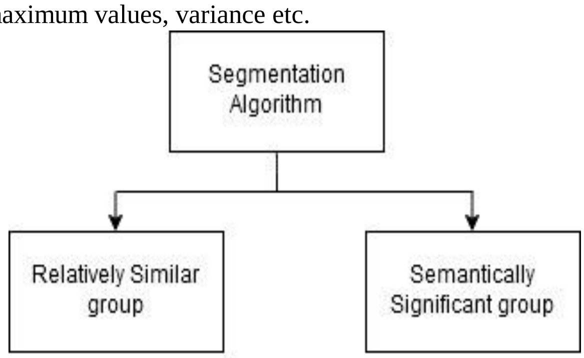

Fig 1. Image Segmentation strategies

B. Image Classification

The image classification methods are broadly categorized into two categories. They are *manual* and *automatic*. The *manual* image classification techniques are strong, efficient and effective. The drawback of these techniques is they consume more time and also the accuracy of the classification purely depends on the analyst who will be very familiar with the areas of the study. The *automatic* methods will employ computer along with image processing techniques with no or little human involvement. These are further categorized into supervised, unsupervised and object-based techniques. Sufficient referential data is a prerequisite to the supervised classification technique. The techniques such as Maximum Likelihood, Minimum Distance, Artificial Neural Network, and K-Nearest Neighbor are listed under this category [7]. In the context of the unsupervised techniques, sufficient referential data as prerequisite is not needed to classify. The classes will be extracted using an iterative process and analysis, by labeling and merging pixels into meaningful classes. The K-Means clustering, Iterative Self Organizing Data Analysis (ISO Data), Support Vector Machine (SVM) are listed in this category.

The main objective of the grouping the pixels into objects is to address the problem known as 'salt' and 'pepper' [8]. This incorporates the contextual information in the classification

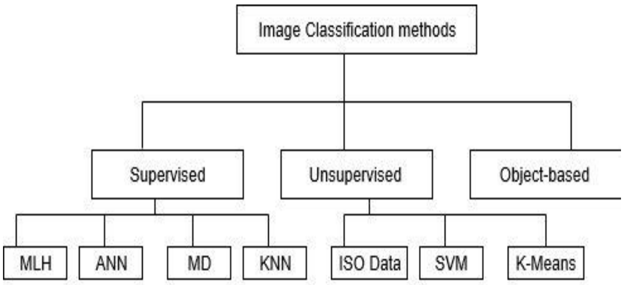

Fig 2 Image Classification Techniques

image to classify landcover information effectively [9].

C. Image Analysis

Image analysis is a process of extracting the quantitative and useful information from the image of interest using the image processing approaches. The quantitative information is used to give answer to questions like "How many?", "How frequently?", "how much?" etc. The image analysis step is generally followed by the image segmentation which groups the pixels of the image based on some similarity. Hence, this step requires the classification rules in order to group the pixels into meaningful groups. The classification rules that have been inducted are now used to classify the pixels into meaningful groups. These groups are then analyzed for quantitative and useful information for both textured and non-textured images.

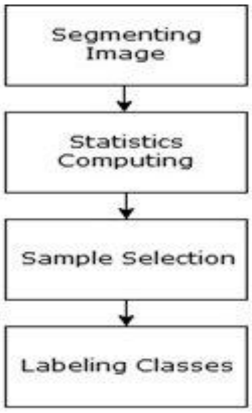

Fig 3 Object-based Image Analysis Process

III. ISSUES IN OBJECT-BASED IMAGE ANALYSIS

One of the common issues with coarse resolution image is that they use to combine the spectral features of heterogeneous landcover. For better understanding the problem with coarse resolution, it can be understood that a resolution image which covers $1KM^2$ can contain mostly forest, but can also contain open patches, roads, orchards, paths, water resources, rocks, and small fens etc.

Most of the cases forest vegetation dominates the other spectral properties. The spectral mixing in images with coarse spectral resolution will push the classification process into confusion. In a situation where some trees cover road area can cause intermixed pixels. It will be very difficult in this situation to determine the pixels to which group it belongs to. To address this problem, an unsupervised and powerful classification method called 'ant colony optimization' is used in this paper.

An object can be identified by shape, size, and pattern [8]. The shape always refers to the outline of the object. If the object class has similar features then it would be trivial to classify the object. If object class has spectral features of other classes then it would be difficult to classify a pixel.

The pattern will form the texture. The texture contains repeated patterns. For example, the water, rocks, grass have some repeated pattern and hence form the textures. This texture helps to build neighboring objects.

IV. WORKING PROPOSED METHODOLOGY OF ACO

Ant Colony Optimization is basically a nature inspired swarm intelligence technique [9]. There are number of swarm intelligence techniques such as Ant colonies, bird flocking, animal herding, fish schooling, bee optimization, etc. These techniques were used to solve many complex. ACO, is one of nature inspired optimization technique. This had solved many complex problems [10] when applied to various fields like data clustering, traveling salesman, finding the shortest path in computer network, data mining and image processing. ACO was derived from the natural behavior of ants. This is an unsupervised clustering technique which does not use parameters during the classification process. In this paper a Hybrid classification algorithm is proposed to classify the pixels of an image. This is powerful and efficient in classifying the pixels into different categories based on the 'pheromone' values which will be computed and is almost for the same class or group of pixels. This mainly works as rule induction algorithm for extracting the rules which later used to analyze the image and different regions of the interest. The algorithm works as shown in the algorithm Fig 4.

a. Algorithm

Step 1: Begin
Step 2: Read image and convert to gray scale image
Step 3: Divide image data into training and test sets
Step 4: Induct classification rules on training set using ACO and fuzzy
Step 5: Test the rules for accuracy on test set
Step 6: Prune the rule list
Step 7: Use refined rules to analyze entire image
Step 8: Extract the regions of interest using the above rules
Step 9: End

Fig 4 Image Analysis Algorithm

b. Classification Rules Generation

The process of rules extraction is quite similar to the collective behavior of ants for finding the food sources. Each classification rule contains two parts: RULE_ANTECEDENT, and RULE_CONSEQUENT. The RULE_ANTECEDENT, is the first half of the rule and defines the condition. The RULE_CONSEQUENT, is the second half of the rule and defines the prediction. The RULE_ANTECEDENT may contain one or more attribute tests (e.g., IF term1 AND term2 AND …termN) that are logically ANDed. The RULE_ANTECEDENT contains only the class prediction (e.g., THEN class1). The term again a triple that contains three parts: attribute, operator and value. The attribute is corresponding to the brightness value of the pixel, the operators can be relational operators such >,<,<=,>=, or = and logical operators such as && and ||. The brightness value ranges from 0 to 255. The rule can contain one or more terms. The rules can be represented in the following way.

Table 1 Classification Rule set

Rule 1: if (A(i,j)>=0 && A(i,j)<=w) then Class1
Rule 2: if (A(i,j)>w && A(i,j)<=2*w) then Class2
Rule 3: if A(i,j)>2*w && A(i,j)<=3*w) then Class3
Rule 4: if (A(i,j)>3*w && A(i,j)<=4*w) then Class4
Rule K: if(A(i,j)>4*w && A(i,j)<=K*w) then ClassK
………
Rule N: if (A(i,j)>5*w && A(i,j)<=N*w) then Class N

The best rules that cover Training part pixels are added to the rule set. The Training samples that are covered by the previous rules are removed from the Training part. The rest of samples in the training set are examined with next order rule. The process of dividing the image data into training and test is done using the 80-20 split respectively. That is 80% of the data is considered for training part and 20% of the data is considered for the test part in general.

ACO is a metaheuristic technique in which a heuristic value will be computed for each pixel is and this value will be almost same for the same group or class of pixels. The heuristic value will be computed for each pixel using the following equation:

$$\eta_j^i = \frac{\sum_{k=1}^{m}(\bar{X}_i^k - \bar{X}_1)}{\sum_{k=1}^{m}\left[\frac{1}{N_i^k-1}\sum_{j=1}^{N_i^k}\left(\left(X_{ij}^k - \bar{X}i\right)\right)\right]} \text{--------}(1)$$

Where, m is number of classes, x_i denotes training set, $\bar{x}_1$ 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. Initially number of classes are extracted using the 2^k general rule [12]. The probability with which a term can be added to the current rule is computed using the following formula:

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

Where, τ_i^j is the value in the amount of pheromone which is constructed from the heuristic values through a repetitive process.

The overall accuracy of the classification model is determined by the Confusion Matrix which looks to be as shown in the Table 2 below:

Observed/ Predicted	Class 1 Predicted	Class 2 Predicted
Class 1 Actual	TP	FN
Class 2 Actual	FP	TN

Table 2 Confusion Matrix

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

V. RESULTS ANALYSIS

Caltech image dataset is used in this research work which contains images of objects belonging to 101 different categories. The Caltech [13] image dataset can be downloaded from the URL https:// www.vision.caltech.edu/image_Datasets/Caltech101. The image “brain_0066.jpg” of size 300X258 is used under the non-textured image category to extract the regions of interest in the image. This image when it is given to the proposed algorithm has 08 different classes of gray level values. Out of these 08 classes 03 classes have contributed very less in analyzing the image. Hence, these 03 rules are removed using i-prune algorithm [13].

Figure 5 (a)

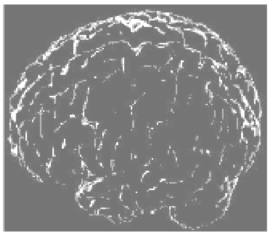

Figure 5 (b)

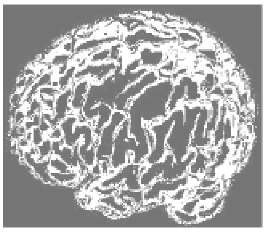

Figure 5 (c)

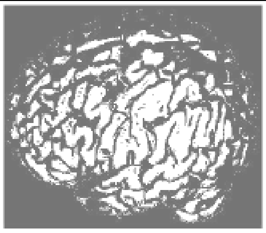

Figure 5 (d)

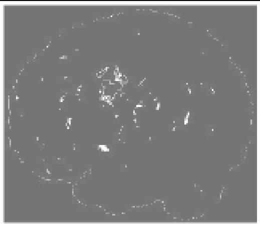

Figure 5 (e)

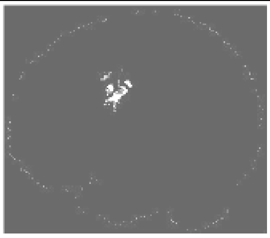

Figure 5 (f)

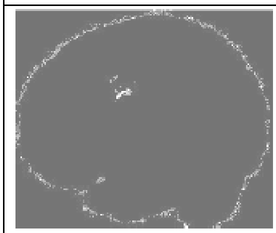

Figure 5 (g)

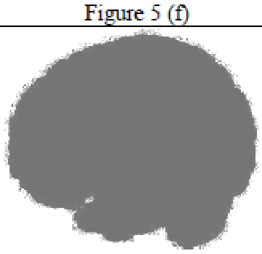

Figure 5 (h)

Figure 5: (a), (b), (c), (d), (e), (f), (g), and (h) are different classes related to different regions of interest in the image

The number of rules obtained using the proposed method is shown in the Table 2. The Number of rules obtained using the other methods like K-Means and ISODATA are also shown in the Table 2.

Table 3 Rules Summary with different methods

Number of Rules obtained through different methods	
Proposed	8
K-Means	15
ISODATA	11

The accuracy of the proposed method is 92.09% accuracy in classifying the gray level values or pixels in contrast with the 84.6% and 87.3% of ISODATA and K-Means methods respectively.

It has been observed that the proposed method when applied to the coarse image has given better accuracy when compared with other unsupervised methods such as K-Means and ISODATA. Hence, the proposed method can be applied to coarse image to extract classification rules which are in turn helpful in analyzing the image to obtain the meaningful information.

VI. CONCLUSION

The proposed approach has ability to address the intermixed pixels problem, which is common in ‘coarse’ images. This unsupervised classification and analysis approach is applied to both textured and non-textured images and has given satisfactory results when compared with other unsupervised approaches as stated in the Results and discussion section. The ACO and Fuzzy has improved the overall classification accuracy when compared with ISODATA and K-Means respectively.

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