Zheng, Hong, Wong, Alan and Nahavandi, Saeid 2003, Hybrid ant colony algorithm for texture classification, *in 2003 Congress on Evolutionary Computation, CEC 2003 : proceedings : Canberra, Australia, 8-12 December, 2003*., IEEE Xplore, Piscataway, N.J., pp. 2648-2652.

Hybrid Ant Colony Algorithm for Texture Classification

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Abstract- This paper presents a novel ant colony algorithm integrating genetic algorithms and simplex algorithms. This method is able to not only speed up searching process for optimal solutions, but also improve the quality of the solutions. In this paper, the proposed method is applied to set up a learning model for the "Tuned" mask, which is used for texture classification. Experimental results on real world images and comparisons with genetic algorithms and genetic simplex algorithms are presented to illustrate the merit and feasibility of the proposed method.

1 Introduction

Image texture analysis and classification has been attracting considerable attention. This is mostly because texture plays an important role in human visual perception and provides information which is used in recognition and interpretation. Texture feature extraction is the most important task in the field of image texture analysis and classification. For the natural texture images , statistical approaches have been widely adopted for texture feature extraction. In the statistical approach, texture is regarded as a sample from a probability distribution on the image space and defined by a stochastic model or characterized by a set of statistical features. The models which have been used to generate and represent textures include: time series models, fractals, random mosaic models, syntactic models and linear models. The most common features used in practice are based on the tonal properties and the pattern properties. These are measured from first- and second-order statistics and have been used as discriminators between textures. Though these features have been widely used in the classification and segmentation of textured images, they are not invariant to changes in rotation and scale. In other words, they are not robust.

Recently, some research presented some new methods to extract adaptive texture features by extending Law's approach [You93][Zheng2000]. In these new method, genetic algorithms were employed to generate texture "tuned" masks, which can be used to extract robust texture features. However, genetic algorithm is weak in local optimization, and sometimes it is difficult to find optimal solution although it is able to quickly find solutions which are close to the optimal solution. In order to solve the problem, this paper presents a hybrid ant colony algorithms to learn the optimal mask for the purpose of texture classification.

The first ant colony optimization (ACO) metaheuristic, called ant system, was inspired by studies of the behavior of ants [Deneubourg83, Deneubourg89, Goss90]. Ants communicate among themselves through *pheromone*, a substance they deposit on the ground in variable amounts as they move about. It has been observed that the more ants use a particular path, the more pheromone is deposited on that path and the more it becomes attractive to other ants seeking food. For example, when an obstacle is suddenly placed on an established path leading to a food source, ants will initially go up or down in a seemingly random manner, but those choosing the side that is in fact shorter will reach the food more quickly and will make the return journey more often. The pheromone on the shorter path will therefore be more strongly reinforced and will eventually become the preferred route for the stream of ants. The works of Colorni *et al.* [Colorni91] and Dorigo *et al.* [Dorigo91,97,96] offer detailed information on the workings of the algorithm and the choice of the values of the various parameters.

The ant colony optimization metaheuristic has been used as a guideline for the design of heuristics dedicated to some combinatorial optimization problem, notably the TSP [Dorigo97], vehicle routing problems [Bullnheimer 99], adaptive control in communication networks [Di Caro98] and graph color problems [Costa97]. However, as far as we know, only few applications to image processing have been published. This paper aims to apply ACO to solve the problem of image texture classification. In this paper, ant colony algorithms, genetic algorithms and simplex algorithms are integrated to build a learning model for optimal mask, which is used to discriminate texture objects on aerial images.

This paper is organized as follows: The ant colony system is outlined in Section 2. Section 3 describes the hybrid learning model for the texture detection mask. Section 4 presents the experimental results and conclusions are given in Section 5.

2 Artificial Ant Colony System

An artificial Ant Colony System (ACS) is an agent-based system which simulates the natural behavior of ants and develops mechanisms of cooperation and learning. ACS was proposed by Dorigo et al. [Dorigo96] as a new heuristic to solve combinatorial optimization problems.

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This new heuristic, called Ant Colony Optimization, has been shown to be both robust and versatile – in the sense that it can be applied to a range of different combinatorial optimization problems. In addition, ACO is a population-based heuristic. This is advantageous because it allows the system to use a mechanism of positive feedback between agents as a search mechanism.

Artificial ants are characterized as agents that imitate the behavior of real ants. However, it should be noted that an artificial ACS has some differences in comparison with a real ACS, as follows [Dorigo96]:

- Artificial ants have memory;
- They are not completely blind;
- They live in an environment where time is discrete.

On the other hand, an artificial ACS has several characteristics adopted from real ACS:

- Artificial ants have a probabilistic preference for paths with a larger amount of pheromone;
- Shorter paths tend to have larger rates of growth in their amount of pheromone;
- The ants use an indirect communication system based on the amount of pheromone deposited in each path.

The key idea is that, when a given ant has to choose between two or more paths, the path that was more frequently chosen by other ants in the past will have a greater probability of being chosen by the ant. Therefore, trails with greater amount of pheromone are synonyms of shorter paths. In essence, an ACS iteratively performs a loop containing two basic procedures, namely:

i) a procedure specifying how the ants construct/ modify solutions of the problem being solved;

ii) a procedure to update the pheromone trails.

The construction/modification of a solution is performed in a probabilistic way. The probability of adding a new item to the current partial solution is given by a function that depends on a problem-dependent heuristic and on the amount of pheromone deposited by ants on this trail in the past. The updates in the pheromone trail are implemented as a function that depends on the rate of pheromone evaporation and on the quality of the produced solution. To realize an ACS one must define [Bonabeau99]:

- An appropriate representation of the problem, which allows the ants to incrementally construct/modify solutions through the use of a probabilistic transition rule based on the amount of pheromone in the trail and on a local heuristic;
- A heuristic function that measures the quality of items that can be added to the current partial solution;
- A method to enforce the construction of valid solutions, i.e. solutions that are legal in the real-world situation corresponding to the problem definition;
- A rule for pheromone updating, which specifies how to modify the pheromone trail;
- A probabilistic rule of transition based on the value of the heuristic function and on the contents of the pheromone trail.

3 Hybrid learning model for "Tuned" mask

In this section we discuss in details our proposed hybrid learning model for "tuned" mask.

3.1 Ant Colony Behaviour Simulation for Mask Learning

In this paper, we extend Law's approach to texture discrimination and segmentation by extending the mask tuning scheme to extract adaptive texture features. In this method, the principle texture statistic utilized to represent the texture feature is the normalized "texture energy" (TE) : the standard deviation of pixel gray scale within a 15*15 window size computed after convolution with a texture "tuned" mask through task-aimed training [You93][Zheng2000]. The tuning procedure of a mask depends on the search algorithm guided by the ant pheromone.

Table 1 lists four candidate masks **I,II,III** and **IV**. We assume that each mask consists of four elements, namely **A1, A2, A3** and **A4** respectively.

Table 1. Four candidate masks and their elements

	A_1	A_2	A_3	A_4
I	13	5	9	17
II	10	5	8	20
III	15	5	9	14
IV	8	8	11	22

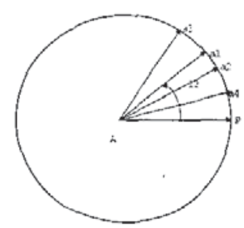

Fig. 1 The distribution map of the mask elements on a circle.

From the viewpoint of ant colony optimisation metaheuristic, searching the optimal elements in the mask can be regarded as searching the optimal path. We define the four elements in the column $\mathbf{A_1}$ as $\mathbf{a_1, a_2, a_3}$ and $\mathbf{a_4}$, which are regarded as the four points on the edge of a circle (see Fig. 1). **A** is the circle centre, vector line **AP** is the original reference direction. The value of each element is regarded as the angle between vector line **AP** and vector line $\mathbf{Aa_i}$ (i=1,2,3,4), so we can locate the elements on the edge of the circle. The greater the difference of element values, the longer the distance between theses element points. Figure 1 shows the distribution map of four element points in the column $\mathbf{A_1}$ on the circle.

Here we assume that there is one ant at each element point, and an ant **S** is going to start from circle centre point **A**. For the ant **S**, the path is chosen accordingly to the quantity of pheromone. Therefore, the position on the circle edge where the ant **S** arrives finally is the place where the pheromone quantity left is most. In other words, the ant **S** finds an optimal path. If we define the position as **T**, the value of the angle between vector line **AT** and **AP** is the current optimal solution. According to this principle, we can obtain the optimal value for each element in the mask through population iteration learning. The simulation algorithm is described as follows:

1. Define an ant population:

   $$\mathbf{X}=\{\, \mathbf{ant_i},\ \mathbf{i=1,2,3,\ldots,N} \}$$

   where $\mathbf{ant_i}$ represents an ant in **X** and its value indicates its position, i.e. the value of one element in the same column of different masks. **N** is the size of the ant population. In the first column of Table 1, for example, N=4, $\mathbf{ant_1}$=13, $\mathbf{ant_2}$=10, $\mathbf{ant_3}$=15, $\mathbf{ant_4}$=8.

2. For each ant $\mathbf{ant_i}$ in **X**, a pheromone is given, namely $\mathbf{w_i}$. The value of $\mathbf{w_i}$ is determined accordingly to the frequency of $\mathbf{ant_i}$ in the **X**;

3. Calculate the possibility that the $\mathbf{ant_i}$'s path is chosen by central ant **S**:

   $$p_i = w_i ant_i \,/\, \sum_{i=1}^{N} w_i ant_i \tag{1}$$

4. The new position possibly chosen by the ant **S** is given by:

   $$ant_{new} = \sum_{i=1}^{N} p_i ant_i \tag{2}$$

5. Add the $\mathbf{ant_{new}}$ into **X**, and repeat step 2~4 to update the pheromone of each ant in **X** and new positions until the pheromone of some ant in **X** is more than a predetermined thredshold **T**. The position of the ant whose pheromone is over **T** is the optimal solution.

6. Apply the above algorithm to each element in the mask until all elements' optimal solutions are obtained.

3.2 The Hybrid Learning Model

Due to the low speed of searching solutions, ant colony simulation algorithms (ACA) is usually integrated with other optimisation algorithms like genetic algorithms (GA). In this paper, we integrate ACA and a new optimisation algorithm named GASPX to speed up searching process and provide high quality solutions.

GASPX is the optimisation algorithms which combines GA and the simplex algorithm (SPX) [Zheng93]. The simplex algorithm is an elegant method for function optimization which, though not strictly "global" (in the sense that it searches all solution space), is able to crawl out of some local optima to find better optima. In other words, SPX is a robust method to search local optimal solution. GASPX employs SPX to improve the GA's ability of local searching and speed up its convergence. For details, see [Zheng2002]. Though GASPX's convergence speed is faster than that of traditional GA, sometimes it is not able to obtain the optimal solution due to SPX's direction characteristic. Thus, this paper integrates ACA and GASPX to present a new optimisation algorithm named GASPXAS. GASPXAS is described in the following:

Step 1: Generate 20 initial candidate masks and their fitness values using GASPX;

Step 2: Sort the 20 candidate masks in descent order and copy the 3 best masks to next generation:

Step 3: Randomly divide the 20 candidate masks into five groups, each of which includes the 3 best masks and 3 masks randomly selected from 17 worse masks.

Step 4: For each group of masks, the ant colony simulation algorithm is used to search one optimal mask. Thus, a total of five optimal masks are obtained, and copied to next generation.

Step 5: Generate 12 offspring with current 20 candidate masks using GA, and copy these offspring to next generation.

Step 6: For new generation population, repeat step 2~5 until determined criterion is met.

Step 7: Output the optimal solution.

Figure2 shows the algorithm flowchart of GASPXAS.

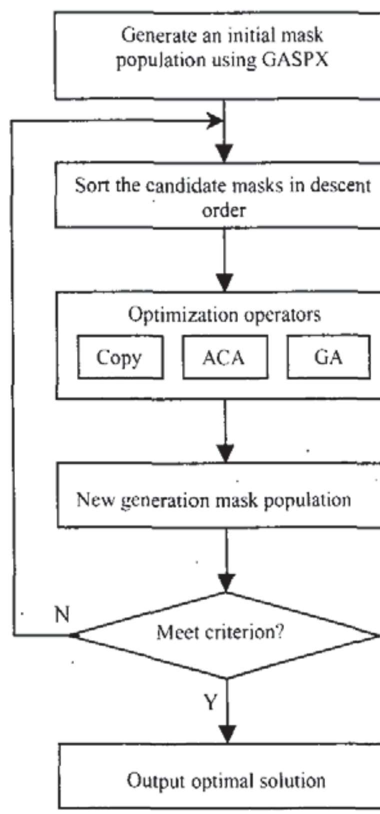

Fig.2 The algorithm flowchart of GASPXAS

3.3 The Classification Based on Hybrid Ant Colony Algorithms

The classification procedure can be divided into two phases: learning phase and implement phase. In the learning phase, the optimal mask is obtained by hybrid ant colony algorithm. In the implement phase, the learned

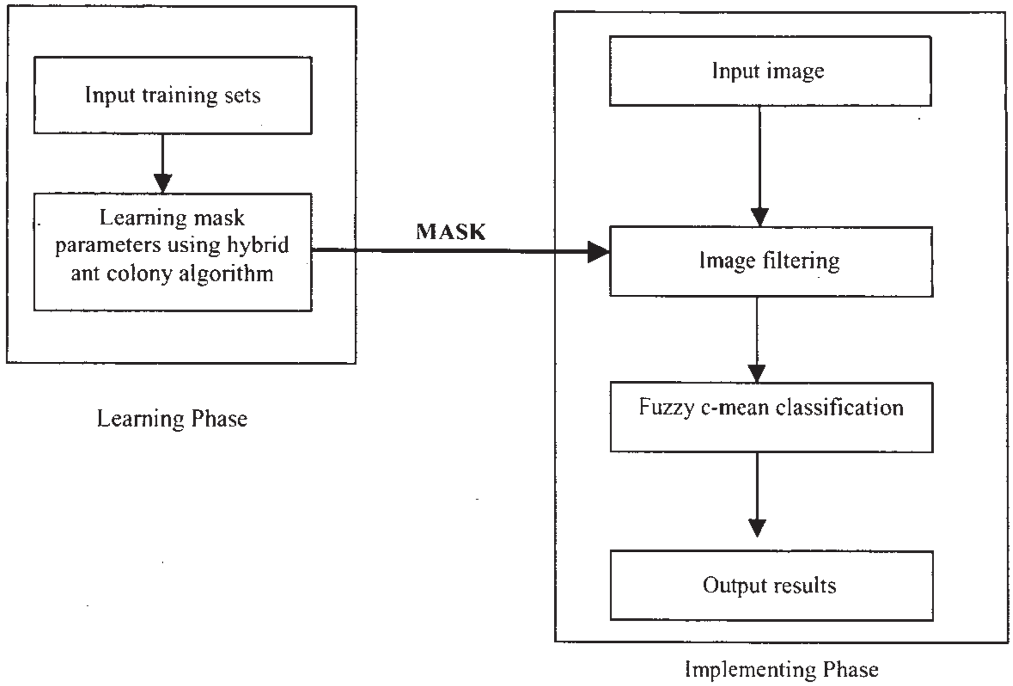

Fig. 3 The classification flowchart based on hybrid ant colony algorithm

mask is employed to filter images and classify the filtered images using fuzzy c-mean method. Figure 3 shows the classification flowchart based on hybrid ant colony algorithm.

5. Experimental Results

In this section we present experimental results of learning optimal mask using GASPXAS. A total of 50 texture images with 100 by 100 size are used to learn the optimal mask. These images consist of resident land, bush, cultivated land, mountain land, and acid land, which are selected from real aerial images. Some of them are shown in Fig. 4. The learned mask is tested on 47 bush images, 23 resident land images, 13 cultivated land images, 20 mountain land images and 15 acid land images. In addition, we compare the classification results with the mask learned by GA ,GASPX and GASPXAS respectively. Table 2 lists the comparison results of classification rates. From Table 2, it can be seen that the classification rate with the mask learned by GASPXAS is the highest. This illustrates that the proposed method is able to obtain better solution than that obtained by GA and

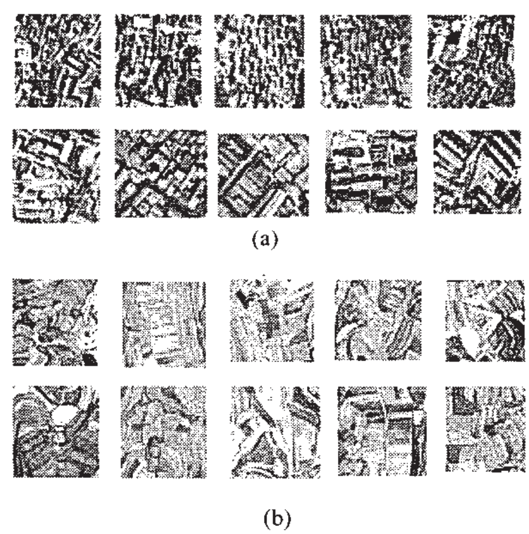

Fig.4 Some trained texture images (a) Resident land images. (b) Cultivated land and acid land images.

Table 2. Classification comparison results using three methods

Method	Bush	Resident land	Cultivated land	Mountain land	Acid land	Average
GA	84 %	82 %	85 %	76 %	81%	81.6 %
GASPX	83 %	86 %	89 %	91 %	82 %	86.2 %
GASPXAS	91%	92 %	95 %	96 %	90 %	92.8 %

GASPX. In other words, the proposed method has more powerful capability of searching for optimal solutions.

We also did 30 learning experiments with GA, GASPX and GASPXAS respectively. The average convergence generation of GA, GASPX and GASPXAS is 31, 12 and 7 respectively. Obviously, the proposed method can speed up the searching process.

5. Conclusions

In this paper we have shown how to apply ant colony behaviour simulation algorithm to generating the optimal mask used for texture classification, and present the hybrid learning model based on ant colony algorithms, genetic algorithms and simplex algorithm. Experimental results are given to illustrate the capability of proposed method.

Proper selection of control parameters for an application of ACS is still an open issue. In this work we selected parameters manually. Further experiments with the adaptive parameter settings of the ACS are necessary. In addition, the ability of proposed approach is limited by training samples, and combination with other texture models and detection methods is not only helpful, but sometimes is also necessary.

It is seen by a survey that the ACS is not used widely to image processing. This initial study, while promising, shows its potential application in the field of image processing. We plan to further implement more properties of ACS for better results and exploit more applications for image processing.

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