The Integration of Cooperation Model and Genetic Algorithm

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1 Introduction

Since the foundation of bionics in the middle of 1950's, inspired from the evolutionary mechanism in natural world, people have proposed a variety of novel approaches, such as genetic algorithm (GA), evolutionary programming, and evolutionary strategy, etc., to complex problem solving and optimization. Genetic algorithm has already been applied to solve a number of problems involving combinatorial optimization, of which the traveling salesman problem (TSP), assignment problem are the paradigms. In recent years, GA has been introduced to the research field of photogrammetry and remote sensing and has been used for such applications as texture-based classification from aerial image data, hyperspectral data redundancy reduction and image matching, etc. Convincing results are obtained from the above experiments. However, GA was found inadequate in cases pertaining to search for the optimal solution — it can rapidly find the solutions close to the optimum but is not easy to get the exactly optimal one because of the effects of these suboptimums. To overcome this defect, people attempted to extract advantages from other algorithms to combine them with genetic algorithm.

This paper proposes to integrate cooperation model with GA to generate "tuned" mask. The term "cooperation" is from synergetics, an intersection research field of physical and social sciences and deals with research on rules and features concerning how a system turns to be structured from a disorganized status through cooperated interactions. And a typical example of cooperation model is ant colony algorithm (ACA).
2 Cooperation model — ant colony algorithm

Ant colony algorithm was firstly proposed in 1991 and used to solve the traveling salesman problem, assignment problem and job-shop dispatch problem. D. Costa and A. Hertz applied the algorithm to solve problems of assignment and graphic tinting respectively.

Ant colony algorithm was introduced from the inspiration based on the study of behaviours in natural ant colonies. The term "ant colony algorithm" is used here to denote "the artificial ant colony algorithm". Artificial ant differs from natural ant in that it has much better memory. Biologists found that although a single ant only has very limited memory and intelligence, the whole ant colony is capable of performing extremely complex tasks by cooperated interactions among ants, which is based on very simple flows of information in form of pheromone trails. The following instantiation illustrates how ants cooperate and communicate individual information and manage to establish shortest route path from their nest to feeding source.

In Fig. 1, A is the nest, and B is the feeding source. From A to B there are two alternative paths, ACB is the longer one, whereas ADB the shorter. A moving ant lays some pheromone on the ground, thus marking the path it followed by a trail of this substance. An isolated ant chooses path for later moving according to the pheromone intensity on each individual path. Fig. 1 (a) illustrates that there are four ants (numbered 1, 2, 3 and 4 respectively) in the nest, and B is the feeding source. At the beginning, Ant 1 and Ant 2 move towards their feeding source. They choose path ACB or ADB with equal probability since no previous ants passed through before and no pheromone was on either of the two paths. We suppose that Ant 1 chooses ACB, while Ant 2 does ADB. If the two ants move in a same constant speed, Ant 1 is still in its tour towards B when Ant 2 reaches B, as illustrated in Fig. 1 (b). When Ant 2 arrives B and turns back, it also makes the back path choosing according to the intensity on each of the possible paths. As Ant 1 is still in its tour towards B and there is no pheromone laid on BCA, Ant 2 is likely to choose ADB, its originally followed path, as its back tour path. When Ant 2 is back to A, Ant 3 is ready to start its tour. As demonstrated in Fig. 1 (c), Ant 3 is definitely to choose ADB because there is more intensive pheromone on it than on ACB (as two ants passed through ADB). Ant 1 will certainly choose BDA as its back tour path (Fig. 1 (d)). As a consequence, there will be more and more ants passing through ADB, and in this way, ants find the shortest path from their nest to the feeding source.

From the above instantiation, it is not difficult to understand that the shortest path from ant nest to their feeding source is established in a cooperated way, in which each ant among the whole colony contributes its share to the pheromone quantity on each possible individual path. The mechanism of the process in which ant finds the shortest path from their nest to the feeding source is much similar to that of traveling salesman problem. Taking TSP problem as a test example makes ACA principle more easily understood.

Given n towns, the TSP problem can be stated as the problem of finding a minimal length closed tour that visit each town only once. In this case, suppose that there are n towns and m ants. Between Town i and Town j, let \( b_i(t) \) (\( i, j = 1, 2, \cdots, n \)) be the number of ants in Town i at time t, then \( m = \sum_{i=1}^{n} b_i(t) \) be the information content on Path \( i \), \( \tau_j(0) = c \) (c is a constant). Ant k moves towards a certain direction according to information content on each path. \( P_{ij}(t) \) is the transition probability from Town i to Town j:

\[
P_{ij}(t) = \frac{\tau_j^\alpha(t) \eta_i^\beta(t)}{\sum_{j \in k, \text{allowed}} \tau_i^\alpha(t) \eta_j^\beta(t)}, j \in k, \text{allowed}
\]

\[
\tau_j(t + 1) = \rho \times \tau_j(t) + \Delta \tau_j, \rho \in (0, 1)
\]
\[ \tau_{ij} = \sum_{k=1}^{n} \Delta \tau_{ij}^k \quad (3) \]

\[ \Delta \tau_{ij}^k = \begin{cases} Q/L_k, & \text{Ant } k \text{ passing through } ij \\ 0, & \text{other} \end{cases} \quad (4) \]

where \( \Delta \tau_{ij}^k \) is defined as the information content that Ant \( k \) laid on Path\( ij \); \( \Delta \tau_{ij} \) is the information content increment on Path\( ij \); \( Q \) is a constant; \( L_k \) is the length Ant \( k \) passed on the current path; \( a, \beta \) are parameters that allow a user to control the relative importance of the accumulated information pertaining ant moving process versus heuristic factor for selecting a succeeding path; \( \eta_{ij} \) is the visibility from Town \( i \) to Town \( j \); \( 1 - \rho \) represents evaporation.

Eqs. (1)-(4) portray the mathematic model of ACA. For different application tasks, \( \tau_{ij}, \Delta \tau_{ij} \) and \( P_{ij}(t) \) may be in different forms. Given \( P_{ij}(t) \), the desired optimum value can be obtained through iterative computation.

The above elucidates the principle of ant selecting its shortest route path from the nest to their feeding source. Its most typical application example is TSP problem, and a good result is achieved.

When ACA is applied to TSP problem, the succeeding town can be determined through computing transition probability according to Eq. (1). If an ant is located in a certain town, but both available succeeding selectable towns from a given town and the distances between every two towns are not known, decision cannot be made through transition probability computing in Eq. (1). For example, the above situation will occur in search for the optimum solution through iteration in a multidimensional space.

In Fig. 2, *\( \text{opt} \) is the optimum location, and \( A \) is the initial position. After iterating \( n \) times, the optimum position *\( \text{opt} \) is obtained, all the intermediate positions \( 1, 2, \ldots, n \) are not known. In this case, ACA is not applicable to search for the position of next better solution using Eq. (1). Does this demonstrate that ACA can not associate with the

Fig. 1 The path of the ant colony

Fig. 2 Finding optimal path in multi-dimensional space
problem to be solved? Of course not. The above introduction, involving both the concepts of communication, cooperation by means of pheromone laid by ants and a computable mathematic model, makes ACA easily understood. The following part elucidates the idea of using ACA for purpose of search for optimum solution in a multidimensional space.

Designing texture classification masks of aerial images, a task, which is to be discussed in this paper, can be considered as a problem of search for optimum solution in a multidimensional space. $5 \times 5$ symmetric templates are used. Each template consists of 10 elements, comprising a point in a multidimensional space, searching for a most suitable mask is searching for optimum solution in the space. First, generate two masks $A$ and $B$ randomly (which must obey the constraints discussed in the following part), compute the corresponding fitness values $f_a$ and $f_b$. Suppose that $f_a$ is greater than $f_b$. Then, the search direction should be $B \rightarrow A$, i.e., the direction in which fitness value increases. Now, suppose that an ant has already arrived at $A$ from $B$ and there are 30 ants gathering there. The next step is using ACA for deciding succeeding move direction. In Fig. 3, $A$ is the nest (there gather 30 ants), the optimum solution should direct to the feeding source. 30 ants move towards the feeding source, the moving direction being random for each individual ant, and after many steps they can reach their feeding source, not like Fig. 1 with only two selectable paths. Choose 10 “better” directions from 30 directions. Here “better” directions mean directions with smaller scalar product representing directions in which solutions near the optimum location. There are ants passing through these 10 “better” directions and laying pheromone which diffuses around. In the average path (the average direction of the 10 “better” directions) pheromone intensity increases, which lead to cooperation among ants. As a consequence, an ant will choose a direction with a higher level of pheromone as its decisive direction to move to and without computing the transition probability as shown in Eq. (1), but the mechanism is the same. Using average direction as decisive direction is the result from communication and cooperation among ants through pheromone.

3 Integration implementation

The integration of GA and ACA is used to automatically generate texture classification masks in the present paper. As to the principle and method, please see Reference [2]. The basic idea of the integration is: First, use GA to the process of search for the optimum from a population with size of 30, when the solution turns stable, introduce ACA into the process for purpose of generating new individuals, and then use GA again, repeat the above operation until the requirement is met.

The problem of using ACA to generate texture classification masks is different from that of TSP. In TSP, the selectable paths are determined, whereas in generating texture classification masks, there are no determined selectable paths for ants to choose and empirical knowledge is needed to help the selecting.

3.1 Ant moving direction decision

1) The implementation of ACA is initialized from the population coming from the result of GA. Suppose that the population size is 30, they can be considered as 30 points in the solution space, each corresponding a fitness value $f_b$ and the largest fitness value $f_{b_{\text{max}}}$ is the currently best solution. In the succeeding iteration better solution will be generated. To guarantee this, connect every point in the solution space with the currently best solution $f_{b_{\text{max}}}$, constituting vectors $\overrightarrow{b_{1}}$, $\overrightarrow{b_{2}}$, $\overrightarrow{b_{3}}$ and $\overrightarrow{b_{4}}$, etc. in Fig. 4. According to the rules of conjugate gradient method in computational methods, the direction of solution gradient (direction perpendicular to solution vector) should be the direction in which a better solution can be obtained. If
the solution space is two-dimensional, the direction of the better solution of \( \overrightarrow{f_{b}} \) should be as the direction of the arrow in bold line in Fig. 4.

2) If there are many selectable directions from a point in a multi-dimensional solution space, what is the strategy to determine the direction of a better solution? According to the rule, scalar product of two vectors is zero, directions of better solutions are a collective, not only one. To make the problem easily understood, suppose that there are only two solution directions, as \( A_1, A_2 \) shown in Fig. 5. If two ants set off from \( A \), one from \( A \) to \( 1 \) and the other from \( A \) to \( 2 \), the pheromone at \( 1 \) and \( 2 \) diffuse about (actually, the pheromone along \( A_1 \) and \( A_2 \) diffuse about), and the pheromone intensity is reinforced in the intervening area of \( 1 \) and \( 2 \), as at "+" in Fig. 5. If another ant, Ant 3, sets off from \( A \), it will certainly select \( A \) "+", the direction with a higher level of pheromone, say the average direction of \( A_1 \) and \( A_2 \). And if there are \( n \) directions (in multi-dimensional space), Ant 3 will select the direction of the average of the \( n \) directions.

![Fig. 4 Moving direction of ant](image)

![Fig. 5 Superposition of pheromone diffusion](image)

The above is the strategy in the integration in which ant selects direction to move using ACA.

3.2 Content of the integration

1) Randomly generate 30 texture masks which are left-right symmetric with the algebraic sum of all the elements equaling to zero and sizing \( 5 \times 5 \). Compute fitness values \( f_{b_i}, i = 1, 2, \cdots, 30 \), iterate 5 times in GA.

2) Take the mask with the maximum \( f_{b_{max}} \) in the current population as the current best solution. Each solution corresponding to a single point in the solution space, the other 29 individuals in the population can be considered as 29 points. If there is one ant at each point, the 29 ants will move towards the direction of the best solution, as shown in Fig. 4.

3) When the 29 ants arrive at the place where the currently best solution locates, the succeeding path should be selected according to the above strategy. The operation is as follows: 10 masks are randomly generated at \( f_{\text{max}} \) for Ant \( i \), constituting 10 scalar product with \( f_{\text{max}} \), as in Fig. 6, \( \overrightarrow{f_{\text{max}} f_i} \), \( \overrightarrow{f_{\text{max}} f_1} \), \( \overrightarrow{f_{\text{max}} f_2} \), \( \cdots \), \( \overrightarrow{f_{\text{max}} f_{10}} \), according to the above rule, use the average of 4 masks with smaller scalar product as the decision direction of Ant \( i \) from \( f_{\text{max}} \). The operation for other ants is the same.

![Fig. 6 Generating 10 directions for vector \( f_{\text{max}} f_i \)](image)

4) The 29 new individuals generated from above operation together with the best solution comprise a new generation with size of 30. Compute fitness for each individual.

5) Repeat Steps 2) to 4) until the requirement is content. The times of iteration or stableness of fitness value can be used to control the computation.

In above introduction to the integration, ant moving direction is determined through cooperation based not upon directly computing \( P_{ij} \) but upon the principle of ACA and human empirical knowledge in the optimizing procedure.

Inversion mutation is introduced to the integrated GA, the operation is as follow. Suppose there ex-
ists a code sized 9 shown in Fig. 7(a), if 2 and 6 in range (0,8) are randomly generated, all the characters located between 2 and 6 are inversed as Fig. 7(b).

|     | a | b | c | d | e | f | g | h | i |
|-----|---|---|---|---|---|---|---|---|---|
| (a) |   |   |   |   |   |   |   |   |   |

Fig. 7 Inversion mutation

4 Experiment and analysis

To testify the validity and efficiency of the procedure integrating GA and ACA for purpose of texture mask classification, the texture images of different types are picked out from previously interpreted aerial images. The picked images are all sized 100 × 100, and they consist of 53 bush lands, 18 paddy fields, 23 residential areas, 20 mountain areas and 15 drought areas. For each texture, select 7 images used as model images, and for every three kinds, generate a texture mask. To testify the capability of the mask in recognizing residential areas, two groups of different contents are needed. One consists of residential area, bush land and paddy field, and the other consists of residential area, drought area and mountain area. Generate two masks in this way, and use the average recognition accuracy of the two groups as the recognition accuracy for residential area. The recognition accuracy is used here to denote the recognition accuracy for residential area to be recognized and the refusal accuracy for non-residential area. The comparison of integrated procedure and single GA is tabulated as Table 1.

| Method  | Bush land | Residential areas | Paddy field | Mountain Areas | Drought areas | Average |
|---------|-----------|-------------------|-------------|----------------|---------------|---------|
| GA+ACA  | 0.91      | 0.92              | 1.00        | 0.96           | 0.98          | 0.954   |
| GA      | 0.84      | 0.82              | 0.85        | 0.76           | 0.81          | 0.816   |

From Table 1, the average recognition accuracy of the integrated procedure of GA and ACA is 0.954, much higher than that of the single GA procedure with average recognition accuracy 0.816. Two points should be noted in the experiment.

1) The classification results are directly associated with the model images from which masks are generated. How to select model images properly needs further discussion;

2) The elements in masks are usually in form of integer, when solution is near the optimum, floating point form will facilitate the search for the optimum. In this case, integer form is subject to stagnancy.

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