2021 13th International Conference on Measuring Technology and Mechatronics Automation (ICMTMA) | 978-1-6654-3892-6/20/$31.00 ©2021 IEEE | DOI: 10.1109/ICMTMA52658.2021.00107

# An Intelligent Teaching Test Paper Generation System Based on Ant Colony Hybrid Genetic Algorithms

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*Abstract*—**In this paper, the problem of intelligent test paper generation is discussed, and the advantages and disadvantages of current commonly used intelligent test paper generation algorithms are analyzed. By comparing genetic algorithm with ant colony algorithm, it is found that the two algorithms have complementary advantages and they can be integrated organically. On this basis, an intelligent test paper generating strategy based on hybrid genetic algorithm and ant colony algorithm is proposed. The experiments show that the convergence speed of hybrid test paper generating strategy is faster than that of single genetic algorithm and ant colony algorithm. Compared with single genetic algorithm and ant colony algorithm, the efficiency and success of hybrid test paper generating strategy are greatly improved, which has better practicability.**

***Keywords-genetic algorithm; ant colony algorithm; test paper generation; GACH***

## I. INTRODUCTION

As a multi-objective and multi-constraint combination problem, test paper generation automatically extracts test questions from the test database to meet a series of requirements of teachers, such as the type of questions, the coverage of knowledge points, the difficulty and the distribution of scores. In recent years, some researchers have studied intelligent test paper generation, and proposed intelligent test paper generation strategy based on genetic algorithm and ant colony algorithm. Although genetic algorithm has potential parallelism and strong global search ability, it does not need a definite model which has strong robustness. However, its local optimization ability is poor in the later stage. It is prone to premature and degenerate phenomena, and the feedback information in the system is not fully utilized. When the solution comes to a certain extent, a large number of inactive redundant iterations are often performed, and the efficiency of finding accurate solutions is low. Ant colony algorithm converges to the optimal path through the accumulation and updating of pheromones. It has the ability of distribution, parallel and global convergence. However, the lack of pheromones at the initial stage of search makes the accumulation time of pheromones longer and the solution speed slower.

This paper combines genetic algorithm with ant colony algorithm, and proposes an intelligent test paper generation strategy based on hybrid approach of the two algorithms. Firstly, a preliminary global optimal solution search is performed based on genetic algorithm, and the global optimal solution information is transformed into pheromone description of ant colony algorithm. Finally, fast and accurate convergence is achieved based on ant colony algorithm. This strategy makes full use of the strong global search ability of genetic algorithm and the high accuracy of ant colony algorithm. It also avoids the defects of genetic algorithm such as insufficient local solution ability, simple premature and degeneration, insufficient use of feedback information in the system, and it also overcomes the shortcomings of pheromone deficiency in the initial stage of ant colony algorithm search.

## II. MATHEMATICAL MODEL OF INTELLIGENT TEST PAPER GENERATION

Intelligent test paper generation refers to that the computer selects a certain number of test questions from the test database to compose the test paper, so the test paper can meet the user's requirements, that is, when composing the test paper, the constraints need to be considered, mainly including the total score of the test paper, the proportion of various types of questions, the coverage of knowledge points, the total time, the difficulty of the test paper and other constraints. Selecting a test question in the process of generating test paper needs to consider n attribute indicators, so a test paper with m number of questions and n attribute indicators for each question can be transformed into a target state matrix of m × n, that is to say, intelligent generating test paper can be transformed into a target state matrix of m × n.

$$A = \begin{pmatrix} a_{11} & \dots & a_{1n} \\ \dots & \dots & \dots \\ a_{m1} & \dots & a_{mn} \end{pmatrix}$$

The constraints conditions needed by object matrix for intelligent test paper generation is

(1) The paper mark constraint $S = \sum_{i=1}^{m} a_{i1}$, whose specific value is assigned as the demand of each paper generation;

(2) Item constraint $Q_t = \sum_{i=1}^{m} c_{ij} \times a_{i2}$, where $c_{ij} = \begin{cases} 1 \ (a_{i2} = t) \\ 0 \ (a_{i2} \neq t) \end{cases}$. t is a question type, which includes selection, filling in the blanks, judgment, short answer, analysis, etc. The specific question type and score are set according to the requirements of each test paper generation;

(3) Knowledge point coverage constraints R= Points of knowledge contained in the selected questions/Points of

978-1-6654-3892-6/21/$31.00 ©2021 IEEE
DOI 10.1109/ICMTMA52658.2021.00107

knowledge that should be included in the exam ⩾ r. Generally, the value of r is recommended as 80%;

(4) Time constraints for answering papers $T = \sum_{i=1}^{m} a_{i3}$, whose special time is set as the demand of each test paper generation;

(5) Difficulty constraints on test paper $D = \sum_{i=1}^{m} a_{i1} a_{i4}$, whose difficulty is set as the demand of each test paper generation.

Intelligent test paper generation is a typical multi-objective optimization problem. The same solution cannot achieve multi-objective optimization at the same time. Therefore, for solving multi-objective optimization problems, the multi-objective optimization is often transformed into a single objective optimization according to a utility function, and solved by the optimization method of single objective function. The weighting coefficient method is used to model the intelligent test paper generation and a weight is given for each objective. Then a new objective function is formed by the accumulation of the weights.

$$g(x) = \sum_{i=1}^{m} w_i \, | \, d_i \, | \tag{1}$$

where $d_i$ is the error of the $i_{th}$ group of paper for generation constraint and $w_i$ is the weight occupied by the $i_{th}$ paper generation object.

## III. Intelligent Test Paper Generation Algorithm Based on Ant Colony Hybrid Genetic Algorithm

### *A. The Principle of Mixing Two Algorithms*

In order to generate the initial pheromone distribution of related problems, we must make use of the rapidity, global convergence and random search of genetic algorithm, which can overcome the shortcomings of the two algorithms and form complementary advantages. Then, to improve the efficiency of solution, we must make full use of the positive feedback mechanism and parallelism of ant colony algorithm. In this way, a heuristic algorithm with better time efficiency and solving efficiency is formed. It is superior to genetic algorithm in solving efficiency and ant colony algorithm in time efficiency, which is called Genetic Ant Colony Hybrid algorithm(GACH). The related research data show that the overall situation of genetic algorithm and ant colony algorithm presents a velocity-time curve as shown in figure 1.

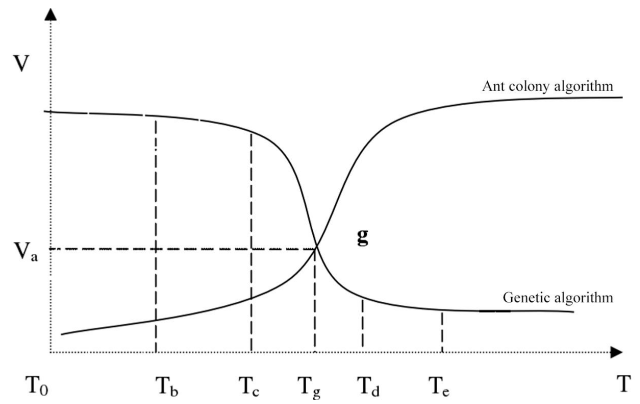

Figure 1. Velocity-time curve

In the figure above, the genetic algorithm has a high convergence rate to the optimal solution at the beginning of the search ($T_0$-$T_b$ period). After T time, the efficiency of finding the optimal solution decreases significantly, and the downward trend is obvious in T. On the contrary, in the initial stage of the search ($T_0$-$T_b$ period), the search speed of ant colony algorithm is slow because of the lack of pheromone. With the increase of the intensity of pheromone accumulation, the convergence speed of its optimal solution increases rapidly. Thus, we get the basic idea of hybrid algorithm fusion: first, we use the fast and comprehensive characteristics of genetic algorithm to generate the initial pheromone distribution in the early stage; then, we use the efficiency and positive feedback of ant colony algorithm to get the optimal solution of the problem after $T_g$ time. Such flow is the process of GACH. The advantage of the combination of genetic algorithm and ant colony algorithm is that it can overcome the inefficiency of genetic algorithm in searching optimal solution and the shortage of initial pheromone plaque of ant colony algorithm when searching to a certain stage. It can also play its respective advantages in searching optimal solution and make up for each other's disadvantages.

### *B. Ant Colony Algorithm Design in Hybrid Algorithms*

The purpose of solving the evolutionary rate repeatedly is to judge whether the termination genetic algorithm is satisfied or not and enter the ant colony algorithm. Evolution rate is defined as the absolute value of the average difference between the parent and the offspring. When the evolution rate of the parent and the offspring is less than Q (which is set to a constant), it indicates that the genetic algorithm enters the invalid redundant iteration calculation stage after this time point, and enters the ant colony algorithm.

Supposing the genetic algorithm acquires a group of optimal solutions containing m elements and the pheromone of the $i_{th}$ tests in the test base at certain hour is $\tau_{ij}$, $j = 1, 2, ..., t$, the position of initial pheromone is set as

$$\tau_{i0}=1+\sum_{n=1}^{m}A_n,\quad A_n=\begin{cases}1/f_n & position\, i\, is\, 0\\ 0 & position\, i\, is\, 1\end{cases} \tag{2}$$

$$\tau_{i1}=1+\sum_{n=1}^{m}A_n,\quad A_n=\begin{cases}1/f_n & position\, i\, is\, 1\\ 0 & position\, i\, is\, 0\end{cases} \tag{3}$$

where $f_n$ denotes the object function or the $i_{th}$ chromosome or global optimal solution.

The pheromone updating method chooses max-min rule. In the traversal process of ant colony algorithm, pheromone is only added to the traversal path of the ant with the highest fitness. The age-dependent relationship of information concentration is expressed by introducing binary group (A, T).

$$A=\{a_{11},a_{12},....a_{m1}..,a_{mn}\}$$

$$T=\{\Gamma(a_{ij},c)\,|\}\Gamma(a_{ij},c)\in R, i=1,2,...,m, j=1,2,...,n\}$$

where $a_{ij}$ denotes a test; $T$ denotes the set of pheromone trajectory; $c$ is 0 or 1. $\Gamma(a_{ij},c)$ denotes the pheromone which is selected or not selected by test $a_{ij}$. $T$ can be expressed by a $2*\sum_{i=1}^{m}n_i$ dimensional matrix as

$$\begin{bmatrix}\Gamma(a_{11},1)\ \Gamma(a_{12},1)...\ \Gamma(a_{1n},1)\ \Gamma(a_{mn},1)\\ \Gamma(a_{11},0)\ \Gamma(a_{12},0)...\Gamma(a_{1n},0)\ \Gamma(a_{mn},0)\end{bmatrix}_{2*\sum_{i=1}^{m}n_i}$$

Ant individual path selection is based on the transfer probability. When the signal is transmitted to one place of the ant, the individual ant decides the transfer direction according to the transfer probability $p_{i0}$ or $p_{i1}$.

### C. Design of Genetic Algorithms in Hybrid Algorithms

The realization process adopts binary coding mode, and the coding set of the same question types are collected together. Assuming there are m types of questions and each type needs to contain $n_i(i=1,2,...,t)$ questions. Its corresponding coding length is $\sum_{i=1}^{m}n_i$ and the coding type is $\{b_{i11},b_{12},....b_{1n}..,b_{mn}\}$.

During the process of hybrid algorithm realization, genetic algorithm and colony algorithm need the same fitness function as

$$F=\max f+\min f-f \tag{4}$$

where the evolution rate is the difference between descendant objective function and parent objective function. The selection operator adopts the biased roulette selection method. The crossover operator adopts the improved single-point crossover method and the mutation operator adopts the 0,1 simultaneous mutation method.

### D. Overall Flow

Step 1: Initialize parameters, and generate initial pheromones according to the optimal solution.

Step 2: Place $h$ ants in their initial combinations. The probability of each ant moving to the next node is calculated, and the next node of the ant is selected according to the probability. Then, each ant searches for the transition probability.

Step 3: After traversing all nodes, the objective function f of each ant is calculated, the current optimal solution is recorded, and all pheromones are updated according to the optimal solution, that is, the optimal ant circle to increase pheromones.

Step 4: If the termination condition is satisfied or not. If it is not, turn to step 2.

Step 5: Output the optimal solution

## IV. Implementation and Analysis of Algorithms

There are six types of questions in the question bank, which are single-choice, multiple-choice, filling in the blanks, judgment, calculation and proof. They belong to five chapters according to their knowledge points. The distribution of the number of questions in each chapter for each type of question in the question bank is shown as table 1. It also stipulates that the score of each item is fixed and the last column in Table 1 provides the score of each item.

Table 1. Distribution of question quantities and single item score for various types of questions

| Types | 1st | 2nd | 3rd | 4th | Total | Item score |
|---|---|---|---|---|---|---|
| Single election | 30 | 70 | 100 | 60 | 40 | 1 |
| Multiple selection | 10 | 40 | 40 | 30 | 20 | 3 |
| Fill in the blanks | 20 | 30 | 40 | 50 | 15 | 2 |
| Judgement | 10 | 30 | 30 | 30 | 5 | 2 |
| Calculation | 5 | 40 | 50 | 35 | 5 | 8 |
| Provement | 5 | 20 | 40 | 20 | 15 | 10 |
| Total | 80 | 230 | 330 | 225 | 130 | |

The answering time of different type and difficulty are listed in table 2.

Table 2. Test answering time

| Type | Very easy | Easy | Moderate | Hard | Very hard |
|---|---|---|---|---|---|
| Single election | 0.8 | 0.9 | 1.1 | 1.1 | 1.3 |
| Multiple selection | 1.2 | 1.4 | 2.1 | 2.1 | 2.4 |
| Fill in the blanks | 1.0 | 1.3 | 1.9 | 1.8 | 2.2 |
| Judgement | 0.5 | 0.7 | 1.0 | 1.2 | 1.3 |
| Calculation | 5.0 | 5.6 | 6.5 | 7.3 | 8.1 |
| Provement | 6.0 | 6.9 | 8.2 | 9.0 | 10.0 |

The GACH are used to generate the test paper separately. The program written by Visual Studio 2015 is used. The effectiveness and superiority of the algorithm are illustrated by comparing the values of objective function. According to the definition of objective function in the article, the smaller value of objective function is, the more successful it is. The results of GA, ACA and GACH test papers are given below.

Table 3 shows the change of the average objective function of ACA running 40 times with value iteration algebra under different ant numbers.

Table 3. GACH test paper generation effects

| Iteration number | 50 ants | 100 ants | 200 ants |
|---|---|---|---|
| 50 | 74.525 | 66.896 | 60.283 |
| 100 | 59.677 | 55.4675 | 50.62 |
| 150 | 49.52 | 42.148 | 41.65 |
| 200 | 42.257 | 37.552 | 31.57 |
| 250 | 31.433 | 27.12 | 21.652 |
| 300 | 22.856 | 18.1975 | 15.66 |
| 350 | 17.781 | 13.517 | 11.077 |
| 400 | 13.645 | 9.875 | 7.518 |

As the number of iterations of evolutionary algebra increases, the objective function values of the three algorithms decrease gradually. In order to better compare the results of the three algorithms, we take the average value of the objective function of the test paper in the case of population size and number of ants, and draw a detailed comparison in the same coordinate plane as shown in figure 2.

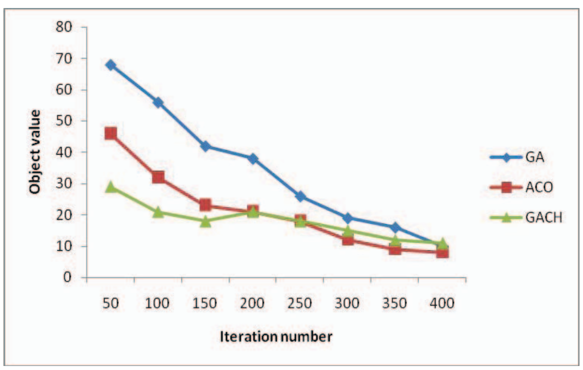


Figure 2. Average object function change curve of three algorithms

As can be seen from figure 1, in the initial stage of evolutionary iteration, the objective function value of GA is smaller, which indicates that the convergence speed of GA is fast; the objective function value of ACA is larger, which indicates that the convergence speed of ACA is slower; the objective function value of GACH is higher than that of GA, but lower than that of ACA, which indicates that the convergence speed of GACH is slower than that of GA, but faster than that of ACA. When the number of evolutionary iterations is more than 200, the objective function value of GACH begins to be less than GA and much less than ACA, which indicates that the convergence speed of GACH is obviously faster than that of GA, and faster than that of ACA. When the number of evolutionary iterations is more than 300, it can be found that the convergence rate gap is small and the advantages of GACH are not obvious at this time. However, the optimization of GACH is better than the rapid convergence of GA and GACH at the initial stage, and it retains ACA and GA very well. Compared with ACA, GACH has better test paper generation effect. This shows that GACH not only inherits the fast optimization performance of later period, but also has better test paper generation effect than GA and ACA.

## V. CONCLUSIONS

This paper analyses the definition, principle, characteristics and basic ideas of genetic algorithm, probes into the advantages and disadvantages of genetic algorithm, and finds out the combination point with ant colony algorithm. Then, the feasibility solution of genetic algorithm is used to optimize the parameters of basic ant colony algorithm, and the idea of combining genetic algorithm with ant colony algorithm is adopted to make full use of the legacy in the early stage of hybrid algorithm. The initial pheromone distribution of ant colony algorithm is formed by the solution obtained by the randomness, global convergence and rapidity of the algorithm. In the latter half of the hybrid algorithm, the optimal solution is obtained under certain initial pheromone distribution by utilizing the characteristics of ant colony algorithm, such as high efficiency, parallelism and positive feedback.

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