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Retraction

Retracted: Research on the Application of Genetic Algorithm in Physical Education

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] H. Wang, "Research on the Application of Genetic Algorithm in Physical Education," *Journal of Mathematics*, vol. 2022, Article ID 8477945, 8 pages, 2022.

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Research Article

Research on the Application of Genetic Algorithm in Physical Education

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University physical education is an important public basic course in colleges and universities. The traditional teaching is usually within the class time specified in the training program; the teacher teaches the students the basic physical education fundamentals so that the students can master the basic skills of sports, thus improving the students' sports level and physical quality. An improved genetic algorithm is proposed to reduce the problem of slow convergence and partial convergence of the fundamental genetic algorithm for intelligent grouping systems. To ensure the group's stability and variety, the algorithm can rapidly extend the search space by repeatedly rejecting similar individuals. Therefore, this study proposes a new method of intelligent grouping based on the improved genetic algorithm. The new method can overcome the problem of premature convergence of the algorithm more efficiently and easily than the traditional algorithm. A large number of experiments have proved that the proposed algorithm meets all the requirements of physical education very well. The algorithm can automatically generate test papers with moderate difficulty and reasonable structure.

1. Introduction

Although Massive Open Online Course (MOOC) has been available in China since 2013 and along with the development of these years, many universities have joined the MOOC team, and the online courses have been growing, but through the survey, we can find that most of the online courses in China are mainly focused on computer, foreign language, and some vocational courses, while the MOOC courses on physical education have just begun in China. This means that MOOC is full of opportunities and challenges for the reform of university physical education in China.

Traditional teaching is usually to teach students the basic knowledge of physical education within the class time specified in the training program so that students can master the basic skills of sports to improve their sports level and physical quality. However, such teaching is very limited, and the teacher-student ratio in many colleges and universities is not sufficient, so the choice of programs in physical education classes is very limited, and many students cannot choose the courses they are interested in, and they cannot satisfy the supplementary physical education knowledge and sports skills training outside the curriculum.

MOOC is a combination of modern Internet technology, computer technology, and mobile technology that allows learning to be accessed anytime, anywhere, and quickly. MOOC is an attempt to superimpose the classroom content on top of this modern information, from massive information to cloud information, making the coverage of physical education content infinitely expandable, which is beyond the reach of traditional physical education content. In addition, the openness of MOOC allows students to access other schools, regions, and even other countries' sports courses in addition to their own sports courses, providing a platform for students who want to master different sports. The openness of the MOOC also allows students to have access to other schools, other regions, and even other countries, providing a platform for students who want to master different sports. At the same time, the MOOC can break the limitations of time and space so that students do not lose the opportunity to learn because of the limited number of students who can take courses and can avoid conflicts in taking multiple courses.

The MOOC courses are organized in a cloud learning environment, which allows students to study in different places and different environments at any time, and with access to mobile terminals, students can access MOOC learning opportunities more freely. Students can study anywhere on campus with their mobile phones, and the same account can be used for intermittent learning, making the learning process both humanized and personalized, making it very easy for students to learn.

The integration of sports training and tactics into traditional physical education has greatly enriched the content, especially by incorporating the latest sports events into the teaching of physical education, which can greatly enhance students' interest in sports. In addition, the most important advantage of physical education classes is that they allow students to choose the content that interests them as much as possible, which is a great complement to traditional physical education classes and makes them more diverse [1].

In addition to benefiting students, teachers can also refer to the content and teaching methods of outstanding scholars in MOOC and improve the traditional and outdated teaching methods in their classes to achieve a more interactive and cooperative way of teaching students. In this way, both students' independent online Massive Online Course (MOC) and teachers' teaching reform in physical education classrooms can greatly increase students' interest in physical activity. In addition, MOOC's easy cloud learning environment allows students to enjoy sports anytime and anywhere, replacing "task sports" with "interest sports" and truly achieving happy sports.

In recent years, optimization algorithms have attracted a lot of attention, such as artificial neural networks and genetic algorithms, among others [2]. It provides new ideas for solving complex problems and has been successful in many fields. Intelligent roll-up is a constrained multiobjective optimization problem. Conventional roll formation algorithms suffer from slow convergence, low success rate, and low quality. Automatic generation systems are always an essential research direction in all kinds of computer-aided testing systems. The efficiency and quality of an intelligent paper-forming system are determined by the algorithm. In this study, we focus on the application of genetic algorithms to combinatorial optimization problems.

The genetic algorithm is based on the principle of natural selection, which is the fundamental law of nature as a whole, and the principle of survival of the fittest and elimination of the inferior. The mechanism of natural selection involves the replication of individuals, the selection of individuals, the inheritance and recombination of individuals, and the variation of individual characteristics. Through these processes, selection can work from one generation to the next, allowing the evolution of the organism to develop in a favorable direction. On this basis, species can accumulate and develop from one direction to another, allowing for diversity in organisms. Thus, through natural selection, populations can be diversified and new species can be created.

Genetic algorithms have a significant advantage over other search algorithms because they are simple to implement, fast in target finding, and strong in coding, making them a good stochastic search algorithm with important applications in many fields. The process of implementation and computation of a genetic algorithm is mainly carried out through several important functions specific to the genetic algorithm, and the direction of the computation is achieved by setting the function and using the adjustment of the direction to achieve the final computation result. In order to improve the genetic algorithm and to achieve the initial effect, it is necessary to study and set the parameters of the algorithm; specifically, in this study, the improvement of genetic algorithm is realized by using race selection in factor operation. On this basis, an improved adaptive genetic algorithm selection mechanism is proposed to enable the target population to operate adaptively so that the genetic algorithm can be used in the first step. This allows the genetic algorithm to converge too early in the early stages or inefficiently in the late stages.

In order to avoid the risk of slow and partial convergence of the basic genetic algorithm for intelligent grouping systems, an improved genetic algorithm is proposed. This algorithm can rapidly expand the search space by continuously eliminating similar individuals and ensure the stability and diversity of the clusters. Therefore, this study proposes a new method of intelligent grouping based on the improved genetic algorithm. The new method can overcome the problem of premature convergence of the algorithm more efficiently and easily than the traditional algorithm. It is proved that the proposed algorithm can meet all the requirements of physical education. The algorithm can automatically generate test papers with moderate difficulty and reasonable structure.

The paper organizations are as follows. Section 2 defines the mathematical models. Section 3 discusses the algorithm design and implementation. Section 4 discusses the analysis of experimental results. Section 5 concludes the article.

2. Mathematical Models

The constraints of the intelligent paper system include overall time, paper score, paper difficulty factor, question type ratio, ability level, knowledge point, regional criteria, and the number of generations. From the perspective of extracting the best combination of questions from a large pool of questions, the intelligent paper-grouping problem is a multiconstraint combination optimization problem. Therefore, if each question has n attributes, combining a study with m questions is equivalent to constructing an objective matrix:

$$s = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{pmatrix}. \tag{1}$$

In the target matrix, each row represents an attribute of a test question, and there are n attributes in total, i.e., n-dimensional vectors. The total score of the study is a_1, the difficulty factor is a_2, the ability level is a_3, the knowledge is a_4, the distribution is a_5, the proportion of questions is a_6, and the completion time is a_7. This is a problem of solving the state matrix, and the target transitions are not unique. The target matrix should satisfy the following constraints:

(1) Total test paper score = $\sum_{i=1}^{m} a_{i1}$ (assigned by physical education, i.e., test paper score constraint)

(2) Difficulty factor = $\sum_{i=1}^{m} a_{i1}a_{i2}$/total score (specified by physical education, i.e., the difficulty constraint of the test paper)

(3) Completion time = $\sum_{i=1}^{m} a_{i7}$ (designated by physical education, i.e., time constraints)

(4) Proficiency level categories (basic understanding, insight and understanding, skill experience, and free play) and scores are assigned by physical education, also known as proficiency level constraints $\sum_{i=1}^{m} c_i a_{i7} = z_p$, where z_p is the p proficiency level of the test score, $c_{1i}\begin{cases} 1 \ldots a_{i3} = p, \\ 1 \ldots a_{i3} \neq p. \end{cases}$

(5) Distribution = $\sum_{i=1}^{m} a_{i1}a_{i5} / \sum_{i=1}^{m} a_{i1}$ (specified by the physical education curriculum, i.e., distribution constraint); question types, knowledge points, distribution, and other constraints are similar to those mentioned above

3. Algorithm Design and Implementation

In this section, we defined the algorithm design and improvement of genetic operations; the crossover operation selects a single-point crossover, mutation operation, genetic algorithm parameters, coding method, elite protection strategy, and algorithm description.

3.1. Algorithm Design. Genetic algorithm was proposed by J.H. Holland, an American scholar. Genetic algorithm is a computational model that simulates the evolutionary process of living organisms in nature. It is gaining attention because of its advantages, such as simplicity, robustness, global search, and fast convergence, and it is not limited by the constraints of the search space. These advantages make it very suitable for the technical problem of intelligent volume formation. The algorithm establishes an initial population of a specific size before inducing crossover and mutation of individuals with a particular probability, resulting in a structural reorganization of individuals. Then, using a specified evaluation function, a new generation is created by picking the finest individuals for replication. The iterations are repeated until a globally optimal solution is found that satisfies the optimization conditions.

Traditional genetic algorithms suffer from low efficiency and tend to generate immature convergence in the later stages of the algorithm. Therefore, many improvement methods have been tried, including designing different choices, cross-variance operations, changing the algorithm structure, designing adaptive cross-variance probabilities, and combining genetic algorithms with other optimization intelligence algorithms. In this study, we propose a method to solve the problem of automatic paper formation with high reliability and validity by globally optimizing the papers in order to finally form the required papers. The results of the algorithm are very good. The specific method is as follows.

3.1.1. Coding Method. The choice of the encoding method is directly dependent on the characteristics of the problem and is an important factor affecting the performance of the algorithm. Common coding methods include binary coding, decimal coding, and real number coding. Because the constraints of the question database directly affect the speed of accessing the database, the algorithm creates a repository file for each question type in order to quickly select the specified question type and reduce the redundancy problem when automatically grouping papers. As a result, the grouped real number encoding method is chosen by the intelligent paper grouping system. Each question type is coded relative to the real number, each code reflects a question type, and the question grouping codes are separate. We mapped a paper to a chromosome and each question to a gene. The gene value can be directly expressed by the number of question types, e.g., in Java programming (5 multiple choice, 5 fill-in-the-blank, 2 short answer, 2 program reading, and 2 programming); then, the chromosome code can be 23, 45, 90, 67, 22, 11, 69, 112, 9, 37, 78, 54, 23, 35, 11, 23. The initial population of the paper was not generated by a completely random selection method, but was generated randomly based on the proportion of questions, total score, completion time, and absence of redundant knowledge points. This accelerates the convergence of the genetic algorithm and reduces the number of iterations. Since different question types are retrieved from different question tables, the same test string number may appear in the same gene string since they belong to different question types. Therefore, this situation is common and does not affect the automatic grouping. Using the grouped real number encoding method, it is able to overcome the drawbacks of too large search space and excessive encoding length in the previously used binary encoding. Also, it enhances the solving speed by eliminating the decoding time of individuals.

The fitness function, also known as the evaluation function, is a criterion used to distinguish between good and bad individuals in a population-based on an objective function. Genetic algorithms use fitness values to guide the search direction, and the fitness function does not require continuous or differential, or other auxiliary information. We use the following form of the fitness function as

$$F = \frac{1}{\left(1 + \sum_{i=1}^{m} k_i \left|e_i\right|\right)}, \tag{2}$$

where e_i corresponds to the i^{th} influencing factor of the constraint paper and k_i corresponds to the weighting factor $k_i > 1$ of the error. This fitness function is able to intelligently group the search features of the paper problem. The smaller the error between the individual paper and the paper constraint is, the closer the individual paper is to the target.

① Improvement of genetic operations: selection operation intelligent group roll system selects the fitness proportion method. The fitness proportion method, also known as the roulette wheel method, is the most common and classical selection strategy in genetic algorithms today. The population size is n, the fitness value of individual i is f_i, and the probability of individual i being selected is shown as

$$p_{si} = \frac{f_i}{\sum_{i=1}^{n} f_i}. \tag{3}$$

Obviously, the greater the proportion of fitness of an individual, the greater the probability of being selected.

② The crossover operation selects a single-point crossover: for two randomly selected chromosomes, a single-point crossover is used to generate random crossover positions in the same type group. If the number of knowledge points and questions is duplicated, the crossover point is then reselected.

③ Mutation operation: the mutation operation also improves on the traditional single-point mutation, i.e., by restricting the genes at each position of each individual to be disordered according to the assumed mutation probability p_m. With the help of the mutation operation, we are able to obtain the target of the local search.

3.1.2. Genetic Algorithm Parameters. The crossover probability p_c and the variance probability p_m of the genetic algorithm have an important impact on the algorithm performance. If p_c and p_m are too large, the algorithm may become a random search. However, if p_c is too small, it may cause a slower search process. If p_m is too small, then it is difficult to generate a new generation and may also cause the algorithm to mature prematurely and get a local optimal solution. We continuously change the crossover probability and variation probability according to the evolution of the population in order to improve the genetic algorithm's search efficiency, avoid local optimum, and protect outstanding individual papers. The automatic adjustment formula in the automatic paper formation system is as follows:

$$p_c = \begin{cases} \dfrac{0.9\left(f_{\max} - f\right)}{f_{\max}}, & f \geq f_{\max}, \\ 0.9, & f < f_{\max}, \end{cases}$$
$$p_m = \begin{cases} \dfrac{0.3\left(f_{\max} - f\right)}{f_{\max}}, & f' \geq f_{\text{avg}}, \\ 0.3, & f' < f_{\text{avg}}, \end{cases} \tag{4}$$

where p_c denotes crossover probability, p_m denotes variation probability, $f_{\max}$ denotes maximum fitness value, f_{avg} denotes average fitness value, f is the greater fitness value of the two crossover individuals, and f is the fitness value of the various individuals. However, for individuals with fitness values lower than the average fitness value, the probability of elimination is relatively high. Therefore, the adaptive p_c and p_m can provide the best crossover probability and variation probability for the individuals of the test paper.

3.1.3. Elite Protection Strategy. After the reproduction, crossover, and mutation operations, the algorithm compares the sufficiency value of the best individual of the new generation with that of the best individual of the previous generation. If it falls, the new generation's poorest individual is replaced by the previous generation's finest individual. This technique protects the best individuals from the effects of reproduction, crossover, and mutation. It is a crucial assurance for the genetic algorithm's convergence.

3.2. Algorithm Description. Parameter settings: maximum number of generations, Max, population size, n, crossover probability, p_c, variance probability, p_m, fitness threshold, M, and input requirements for physical education in an automatic grouping.

In this study, the adaptive selection mechanism and the selection operator are used to calculate the individuals that meet the requirements, to adjust the scale of the competition adaptively, to make timely adjustments according to the variation operation in the process of the competition, to solve the shortcomings of the traditional genetic algorithm of too fast convergence and orientation, and to ensure that the final optimal solution can be obtained in the genetic algorithm. The framework of the algorithm is improved, and the optimal retention strategy is integrated so that the good computational process of the algorithm can be well retained and inherited to ensure that the individuals obtained are in line with the requirements of physical education.

The whole process of the above algorithm can be expressed in the following steps:

Step 1: first, initialize the evolutionary algebra and set it to 0 to start the initialization of the species population

Step 2: adaptation calculations were then performed, mainly for the individual

Step 3: if the end condition is not met, the calculated fitness value and the adopted strategy complete the selection step; the crossover in the genetic algorithm is performed, and if the result of the check meets the requirements of the relevant settings of the intelligent group roll, the operation can be performed; if it does not, it returns; after completing the crossover operation, the mutation operation is performed; the selection mutation operation is performed, and the next generation of individuals is successfully obtained through the above operation. If the new individual has a better fitness than all the individuals, the new individual is set as the best individual and the results and values are saved. If not, we proceed to the next step. The process is shown in Figure 1.

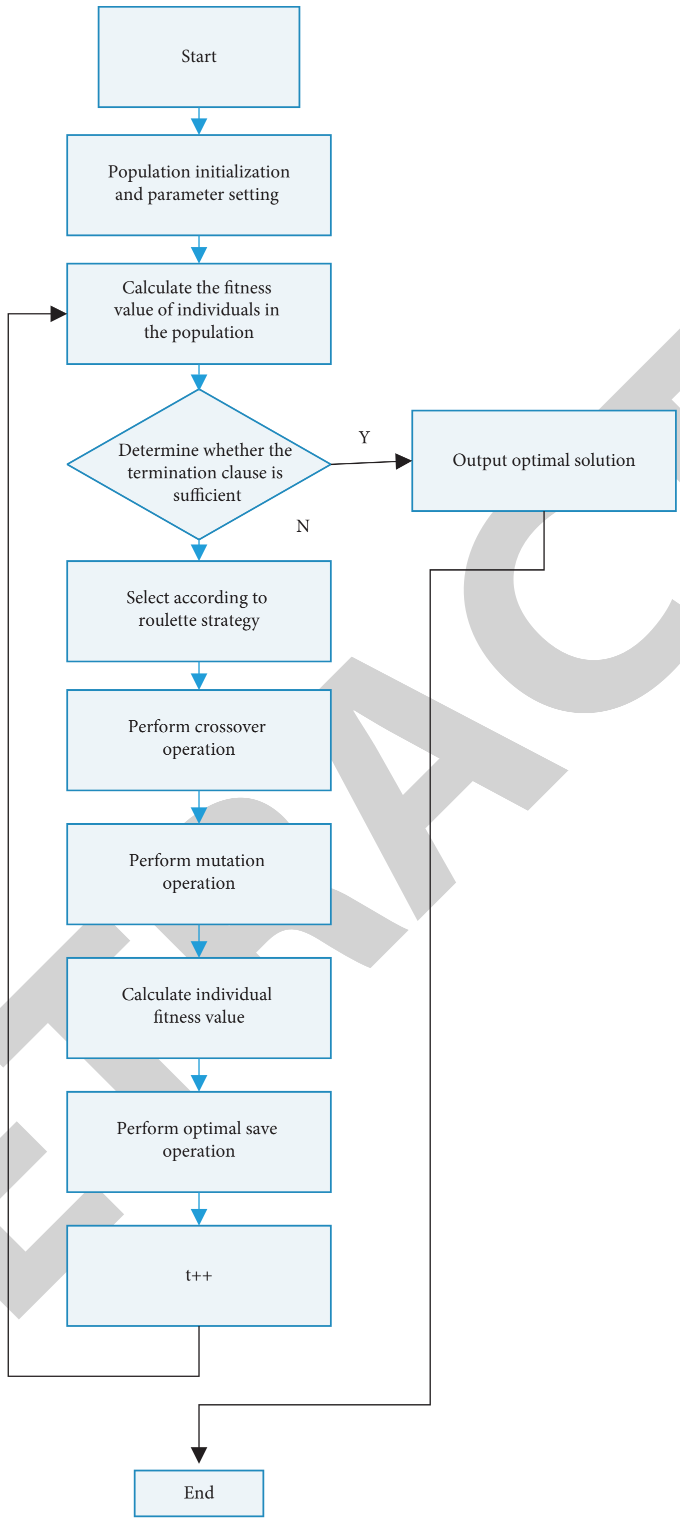

Figure 1: Improved genetic algorithm.

4. Analysis of Experimental Results

4.1. Parameter Setting. For the above improved genetic algorithm, the algorithm implementation steps detail each stage of the algorithm and the specific improvement details of each stage, and after the above operations, the improved genetic algorithm can obtain good individuals. In order to verify the effectiveness and efficiency of the improved genetic algorithm, the test bank of the computer course is used as the dataset for testing the algorithm in this section. In the course "Computer Applications Fundamentals," there are 1000 questions in the database with the following properties and contents.

First of all, there are four types of questions in the dataset of the course test bank, namely, single-choice, multiple-choice, judgment, and fill-in-the-blank questions, as shown in Table 1.

Secondly, there are five chapters in the course, as shown in Table 2.

The only requirement for the knowledge points is that they should not be duplicated when assembling the papers. In addition, in practice, the time of the algorithm needs to be as short as possible so that physical education does not have to wait too long for the paper to be formed, and thus, the efficiency of the intelligent paper formation system can be improved. In this study, the error value for generating test papers is set at 5%.

4.2. Algorithm Testing. In the abovementioned test generation table, the IDs, scores, difficulties, chapters, etc., of each question type are listed in detail in the database. The above data can be used to generate the actual scores for each chapter, the actual scores required for teaching, and the scores' set for each difficulty level which is shown in Tables 3 and 4.

The actual scores of the teaching requirement degree are shown in Table 4.

The scores for each difficulty level were set as shown in Table 5.

After the above operation, we can conclude that the improved adaptive genetic algorithm has good algorithm performance and can complete the extraction and distribution of the difficulty of the test questions in the test bank according to the requirements of physical education, so as to complete the requirements of physical education. Therefore, in general, the adaptive genetic algorithm is a better algorithm for paper composition.

4.3. Comparison of Tests before and after Algorithm Improvement. Through the above analysis, it can be seen that the improved genetic algorithm is able to achieve the functional requirements of physical education in the intelligent grouping environment. For the above results, we need to take more rigorous algorithm testing and comparison, through the way of experimental data to effectively compare the improved algorithm with the algorithm before the improvement; here, we mainly take the improved genetic algorithm and the standard genetic algorithm to conduct experiments and analyze the experimental data; the simulation test is shown in Figure 2.

In this study, the standard genetic algorithm before improvement is represented by GA and the improved genetic algorithm is represented by AGA. The effectiveness and performance of the algorithm can be analyzed in the above way, specifically by the evolutionary generation of the algorithm and the convergence performance of the algorithm. From Figure 2, we can see that the evolutionary algebra of the AGA algorithm is significantly lower than that of the GA algorithm when the number of experiments is 1, 2, 4, and 5. As long as the

Table 1: Question-type setting.

Question type	Quantity	Score
Single-choice questions	20	2
Multiple-choice questions	10	2
Judgment question	10	2
Completion	10	2

Table 2: Score of each chapter.

Chapter	Score
1	10
2	15
3	25
4	20
5	30

number of experiments is 3, the evolutionary algebra of the GA algorithm and the evolutionary algebra of the AGA algorithm are comparable.

Then, for the convenience of programming, the functions are set to their global maximum values, and then, the parameters for the algorithm to run are set as shown in Table 6.

The algorithms are run 50 times according to each run parameter in Table 6, and the algorithms are stopped if they reach the termination condition. The average, minimum, and global convergence probabilities of the two algorithms are shown in Table 7.

From Table 7, the average number of generations of convergence of the improved genetic algorithm is 32 and the average number of generations of convergence of the standard genetic algorithm is 57, and the average number of generations of convergence of the improved genetic algorithm is 25 less than that of the standard genetic algorithm. The upgraded genetic algorithms minimum number of generations of convergence is 24, while the regular genetic algorithm's lowest number of generations of convergence is 39. The upgraded genetic algorithm's lowest number of generations of convergence is 15 times lower than the regular genetic algorithms minimum number of generations of convergence. The global convergence probability of both algorithms is 100%.

Figure 3 shows the ratio of the convergence curves of the two algorithms.

Using the above data test set to compare the degree of convergence of the improved genetic algorithm and the standard genetic algorithm, it can be found that the improved genetic algorithm can obtain the optimal solution in terms of fitness and has a clear advantage in terms of the number of generations of evolution and can converge faster; therefore, the improved genetic algorithm has better advantages and further verifies that the algorithm is feasible and effective. Therefore, the improved genetic algorithm has better advantages and further verifies that the algorithm is feasible and effective and has the advantage of operational efficiency of the algorithm.

Table 3: Sections.

Chapter	1	2	3	4	5
Score	10	16	24	20	30

Table 4: Teaching practical requirements' score.

Teaching requirements	Understand	Application	Analysis	Comprehensive	Evaluate
Score	20	24	20	20	10

Table 5: Difficulty scores.

Difficulty level	1	2	3	4	5
Score	12	30	32	20	8

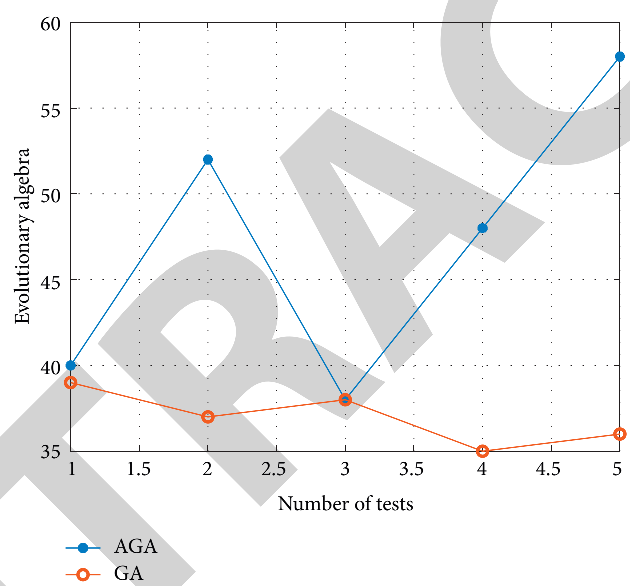

Figure 2: Comparison of the evolutionary algebra of algorithms.

Table 6: Operating parameters.

Algorithm	Population size	Maximum number of iterations	Crossover probability	Variation probability
GA	20	200	0.85	0.10
AGA	20	200	Pcl = 0.85 Pc2 = 0.85	Pml = 0.85 Pm2 = 0.85

Table 7: Experimental results.

Algorithm	Average convergence algebra	Minimum convergence algebra	Global convergence probability (%)
AG	57	39	100
AGA	32	24	100

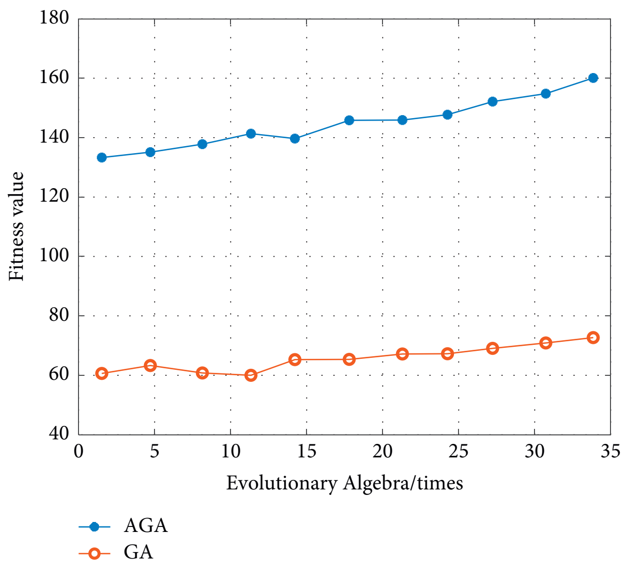

Figure 3: Convergence curve of the algorithm.

5. Conclusions

The performance of the intelligent volume grouping system mainly depends on the performance of the algorithm. The success rate of the traditional algorithm is low, and the constraints of the system cannot be too complex, and the time and space consumption of resources is large. If the improved genetic algorithm is applied to the intelligent volume system, the success rate and convergence speed of the system will be significantly improved. The improved genetic algorithm can realize parallel search in large space. In addition, the algorithm is able to orient the search to the search space that may contain the optimal solution during the search process. Therefore, the optimal solution can be found easily. Moreover, the algorithm should be able to satisfy the complex test paper constraints. As the experimental results show, the algorithm is able to produce a satisfactory test paper with relatively few errors when it evolves to about 32 generations. Therefore, the improved genetic algorithm is much more efficient in solving the intelligent paper formation problem.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares no conflicts of interest.

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