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Research on multi-objective dynamic planning path modeling for college students' career choice in employment and entrepreneurship

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ABSTRACT

The employment and entrepreneurship career choice planning of college students is an important constituent module of the talent training system of colleges and universities in the new era. Aiming at the traditional ant colony algorithm with poor realm adaptability and a large number of inflection points, this paper proposes an ant colony algorithm based on Sigmoid statistical iteration. The Sigmoid activation function distribution strategy is adopted to reduce the blindness of the algorithm's pre-search, and the heuristic function is dynamically adjusted by the introduction of the adaptive factor to reduce the convergence time of the algorithm, and finally the pheromone update function is dynamically adjusted according to the number of iterations to construct the career choice path planning model and apply the model to the career choice planning path recommendation system. When the number of users is 1000, the average response time of the proposed system is only 322ms, the throughput is 394, and the pass rate is 100%, and the CPU occupancy and memory usage are lower than those of the traditional system (35.32% and 39.83%).

Keywords: ant colony algorithm, sigmoid activation function, adaptive factor, career choice

1. Introduction

In recent years, with the number of Chinese college graduates climbing year by year, the employment pressure faced by college students in major universities is also increasing [1]. Career planning and selection is not only an important issue in front of every college student, but also a major challenge for colleges and universities to effectively guide and help students make better choices [2]. Actively improve the construction of talent training system, adopt targeted employment strategy, attach great importance to the output of high-quality talents, and help graduates to timely understand the prospects of industry development and employment planning has become one of the important objectives of talent training in colleges and universities [3-6]. With the continuous development of the

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economy, the transition towards digitalization, many enterprises are facing new situations such as transformation, new jobs are emerging, and the demand for high-quality talents is gradually increasing [7-9]. In terms of the personal development of college students, learning advanced professional knowledge is particularly important to be placed in the position of the top priority, personal ability and technical development directly affects the implementation of their employment issues, the enhancement of the quality of the future career development is crucial [10-13]. Career planning and choice of career play an important role in the future career development path, which is related to the individual's sense of satisfaction, sense of achievement and sense of well-being, these internal feelings affect the individual's behavior and results, and the individual's behavior affects the contribution to the group, organization, and even the whole society and the country [14-18]. Therefore, the correct treatment and handling of individual career choice is an issue that cannot be ignored for individuals, organizations, and societies at any time and any place [19-21]. Especially in the context of the era of great changes of the fourth industrial revolution, it is of great practical significance to explore the issue of career choice for college students' employment and entrepreneurship.

A large number of domestic and foreign related literature has studied the influencing factors of college students' career choice. Literature [22] explored the influencing factors affecting college students' career decision-making skills and used them to establish a model of career decision-making ability, which develops college students' job-seeking skills according to the measurement results, which is conducive to enhancing their self-knowledge, career exploration and self-confidence, and helps them to make better career choices. Literature [23] proposes an intervention model for career choice in the context of technological expansion and economic development, combines cognitive psychology and vocational psychology to form a decision-making model, and considers a comprehensive assessment method and preparation for career interruption to provide decision-making advice for sustainable career choices for users. Literature [24] discusses the relevant factors affecting college students' career decision-making based on Social Cognitive Career Theory (SCCT), indicating that work values, career decision-making self-efficacy, and career goals play an important mediating and moderating role in promoting college students' career choices, and provide directions and paths for college and university parenting. Literature [25] investigated the influencing factors and their differences in the division of college students' career decision-making groups using latent class growth analysis, and found that the direction of college students' career choices was altered by their independent learning experiences and abilities, and differed from the understanding of ideal careers. Literature [26] assessed the validity of entrepreneurship as a career choice by analyzing the relationship between entrepreneurial intentions, attitudes, and outcomes through SCCT, which provided a valid explanation of the entrepreneurial career decision-making model. Literature [27] examined the impact of entrepreneurial awareness on attitudes toward self-employment career choice among college students, which helps universities to develop management and intervention strategies to foster positive entrepreneurial attitudes to promote college students' career choices.

Facing the limitations of the traditional ACO algorithm in career multi-objective dynamic path planning, this paper improves it in terms of initial pheromone distribution, heuristic function, and pheromone update, and proposes an improved ACO algorithm based on Sigmoid statistical iteration. The Sigmoid activation function distribution strategy is adopted for the initial pheromone distribution to realize non-uniform distribution and reduce blindness; the heuristic function is improved and the adaptive factor and the distance information from the candidate nodes to the goal point are introduced so as to increase the goal-orientation of the path search. Combined with the information exchange within the colony population, the three characteristic parameters of the optimal, worst and average ant paths are extracted for each generation. The pheromone update rule is dynamically adjusted according to the number of iterations to balance the relationship between convergence speed and jumping out of the local optimal solution. Based on the improved ant colony algorithm, the career choice planning path recommendation system is constructed to realize the overall architectural design of the information service strategy layer, information service platform layer, and information data warehouse layer, and the user model is constructed from the aspects of information collection, model creation, extraction ensemble, and data processing. The B/S architecture is used to complete the design of the service platform module of the system. Finally, the career choice planning path recommendation system constructed in this paper is tested to verify the effectiveness of the system in this paper.

2. Traditional Ant Colony Algorithm

Ant colony algorithm is a heuristic algorithm based on simulating the behavior of ant colonies and is widely used to solve combinatorial optimization and path finding problems [28].

Path distance and pheromone are the more important parameters of ACO algorithm. The algorithm needs to be modeled before path planning, and the specific steps are shown below.

Step 1, variable initialization. The ant colony algorithm needs to initialize the relevant parameters before performing the task, for example, the pheromone importance parameter is a, the heuristic factor importance parameter is b, the number of ants is m, and the maximum number of iterations is NC_max. To guarantee the accuracy of the data obtained after the algorithm processing.

Step 2, set the neighbor matrix D. D denotes the distance of two of the target points in the indoor environment where the robot is located, and c denotes the coordinates of the two target points. The adjacency matrix is shown in equation (1):

$$D(i,j)=\sqrt{(c(i,1)-c(j,1))^2+(c(i,2)-c(j,2))^2} \tag{1}$$

Step 3, Assume that the total number of ants is m. m ants are randomly placed at n target points, and the effect of the pheromone concentration on the paths determines that the ants move from one target point to another, and the ants forage for food according to their paths. The paths traveled by the ants are recorded, and the state transfer probability of ant k moving from target point i to target point j at moment t is:

$$p_{ij}^{k}(t)=\begin{cases}\dfrac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum\limits_{s\in allowed_k}\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)} & j\in allowed_k \\ 0 & j\notin allowed_k\end{cases} \tag{2}$$

In the formula, $allowed_k$ is the set of target points of ants k in the optional path; α is the information heuristic factor, which indicates the degree of influence of pheromone on the path on the ants' selection of the path, and the larger the value of α is, the stronger the role of pheromone; β is the expectation heuristic factor, which indicates the degree of importance of the distance of the next target point in guiding the colony to search for the path, and the larger the value of β is, the closer the transfer probability of the colony is to the greedy algorithm; $\tau_{ij}(t)$ is the concentration of pheromone between target points i and j; $\eta_{ij}(t)$ is the heuristic function that takes the reciprocal of the Euclidean distance between the target points i and j, as shown in equation (3):

$$\eta_{ij}(t)=\frac{1}{d_{ij}} \tag{3}$$

Step 4, the algorithm undergoes the first processing, records the resulting iteration data, and calculates the path planning distance after the current round of iterations.

Step 5, update the pheromone. Since the ACO algorithm is a positive feedback algorithm, the pheromone on the path accumulates and becomes larger over time, resulting in the weakening of the heuristic function until it finally disappears. Therefore, the pheromone needs to be updated. The pheromone update adopts two ways: real-time pheromone update and path pheromone update. Pheromone updating means that each ant in the colony updates the pheromone of the path target point after arriving at the path target point chosen by the ant, and the updating calculation formula is:

$$\tau_{ij}(t+1)=(1-\rho)\tau_{ij}(t)+\rho\tau_0(t) \tag{4}$$

where τ_0 is the initial value of the target point information; the adjustable parameter $\rho\in[0,1]$ is the volatilization coefficient of the pheromone. Path pheromone updating refers to updating the pheromone in path (i,j) after all ants have traveled the path from the start point to the end point and completed an iterative search in the ACO algorithm, and the updating pheromone is calculated as:

$$\tau_{ij}(t+1)=\rho\tau_{ij}(t)+\sum_{k=1}^{m}\Delta\tau_{ij}^{k}(t) \tag{5}$$

where there are three pheromone updating models in $\Delta\tau_{ij}^{k}(t)$, namely the ant perimeter model, the ant quantity model and the ant density model. Define parameter Q as a pheromone constant, which represents the total value of pheromone secreted by an ant after traversing all processes.

1) Peripatetic model. The ant perimeter model calculates the pheromone increment of each segment of the path by the total length of the path of the ant after each search, as shown in equation (6):

$$\Delta\tau_{ij}^{k}=\begin{cases}\dfrac{Q}{L_k} & \text{Ant } k \text{ goes through the path between } i \text{ and } j\\ 0 & \text{else}\end{cases} \tag{6}$$

where L_k denotes the sum of all path lengths passed by ant k rounds. The ant week model is to utilize the overall result to complete the updating of the global pheromone, the less the path length, the larger the pheromone increment, the more obvious the updating effect.

2) Ant volume model. The ant-volume model is based on the local path length and at the same time according to the total amount of pheromone to complete the update of the local pheromone, as shown in equation (7):

$$\Delta\tau_{ij}^{k}=\begin{cases}\dfrac{Q}{d_{ij}} & \text{Ant } k \text{ goes through the path between } i \text{ and } j\\ 0 & \text{else}\end{cases} \tag{7}$$

3) Ant-dense model. The ant-dense model does not consider the effect of path length on pheromone updating, which adds pheromone in the form of a fixed value, as shown in equation (8):

$$\Delta\tau_{ij}^{k}=\begin{cases}Q & \text{Ant } k \text{ goes through the path between } i \text{ and } j\\ 0 & \text{else}\end{cases} \tag{8}$$

3. Career choice path planning model based on improved ant colony algorithm

The traditional ant colony algorithm (ACO) in the path planning of career choice has the problems of poor environmental adaptability, high number of inflection points and high computational complexity, which can not efficiently obtain the optimal path. In this chapter, an ACO based on Sigmoid statistical iteration is proposed to improve the traditional ACO and construct a path model for career choice planning based on the improved ACO.

3.1. Sigmoid activation function distribution strategy

In the traditional ant colony algorithm, the initial pheromone concentrations of the raster map nodes are equal, which will lead to a lack of guidance for the ants, which may explore some wrong paths, thus reducing the search efficiency. To solve this problem, the Sigmoid function initial pheromone update method is introduced, which effectively guides the ants to converge to the optimal solution more rapidly in the search space by setting a non-uniform initial pheromone concentration mapped to a specific interval [29].

Sigmoid function is a commonly used nonlinear activation function. The function is characterized by smoothness and adaptability, and can adjust the pheromone distribution strategy according to the specific problem. It enables the ants to better distinguish the advantages and disadvantages of different paths during path selection, and improves the diversity and convergence of the algorithm.

The sigmoid function transforms the initial pheromone concentration from a fixed value to a variable related to the position of the grid node. It guides the ants to choose the path at the starting point with more diversity and randomness, which is conducive to exploring the search space; when choosing the path close to the goal point, it gives full play to the guiding role of the pheromone, so as to improve the algorithm's ability of searching for the global optimal solution, and to obtain the multi-objective dynamic planning paths for the college students' employment and entrepreneurship career choices.

The expression of the initial pheromone $\tau(0)$ is:

$$\tau(0)=S(x)=q_0\left[1-\frac{1}{1+e^{-(x-d_{svg})}}\right] \tag{9}$$

$$d_{avg}=\sqrt{(x_s-x_e)^2+(y_s-y_e)^2}\,/\,2 \tag{10}$$

where: q_0 is the initial pheromone concentration; x is the Euclidean distance from the current node i to the target node j; d_{avg} is the average distance from the start point (x_a,y_s) to the target point (x_e,y_e).

The improved algorithm sets different initial pheromone concentrations according to the size of the environment map q_0. Analyzing Eq. (5), it can be seen that when x is smaller, the ants rely more on the heuristic function information in the path selection to avoid the interference caused by the initial equal pheromone on the ants' optimization search. On the contrary, when x is larger, the ants are closer to the goal point, and at this time, moderately increasing the pheromone concentration of the nodes near the goal point helps to improve the convergence speed of the algorithm, so that the ants can find the optimal solution of the multi-objective dynamic programming for college students' career choices more quickly.

3.2. Improving the Distance Adaptation Factor

The heuristic function in the traditional ant colony algorithm uses the Euclidean distance between the grid nodes as the update parameter [30]. However, in the eight-neighborhood search method, when the raster length is set to 1, the result of the heuristic function is limited to the two cases of 1 and $\sqrt{2}\,/\,2$.

In the early stage of the search path, the ant's search strategy mainly relies on the heuristic function, and strengthening the dominant role of the heuristic function can effectively improve the convergence speed of the algorithm. However, when the transfer probabilities are similar, the effect of the heuristic function will be weakened, which reduces the diversity of the ants' selection paths and adversely affects the global search performance of the algorithm. Therefore, the heuristic function is improved in this paper to enhance its guiding role. When the ants make the next grid selection, in addition to considering the Euclidean distance between the current node and the candidate node, the distance between the candidate node and the target point is also taken into account and added to the heuristic function, which guides the ants to shorter paths by increasing the difference between the heuristic functions on different candidate nodes, and the improved heuristic function is:

$$\eta_{ij}(t) = \frac{u}{(1-\zeta)d_{ij} + \zeta d_{js}} \tag{11}$$

$$u = 1 - \frac{N}{N_{\max}} \tag{12}$$

where: d_{ij} is the Euclidean distance from the current node i to the candidate node j; d_j is the Euclidean distance from the candidate node j to the target point S; ζ is the distance weight coefficient used to regulate the impact of the target point on the heuristic function; u is the regulating factor; N is the number of current iterations; $N_{\max}$ is the maximum number of iterations set by the algorithm.

Analyzing equation (8), it can be seen that in the early stage of the algorithm iteration, when u is close to 1, the enhancement of the heuristic function can accelerate the convergence speed of the algorithm.

In the later stage of the algorithm iteration, when u is close to 0, the heuristic function is reduced to avoid local optimization, improve the global search ability of the algorithm, and realize the multi-objective dynamic path planning of college students' career choice.

3.3. Improvement of pheromone update rules

There are two main steps in the construction of solutions for traditional ant colony algorithms, the construction of individual ant solutions and the exchange of information among the colony. The construction of individual ant solutions improves the diversity of the algorithm, and the information exchange helps the whole colony to find the global optimal solution. However, in practical applications, this solution method has some obvious defects. First, the traditional ant colony algorithm uses the same pheromone updating method in each iteration, which cannot be dynamically adjusted according to the characteristics of the problem and the changes in the search process, and cannot satisfy the diverse and changing needs of college students in the choice of employment and entrepreneurship careers. In addition, the pheromone update is limited to the local optimal solution of the current iteration, ignoring the possibility of the global optimal solution, and the algorithm may converge prematurely, thus failing to find the optimal solution and provide the optimal career planning path.

In order to better optimize the performance of the algorithm, the ACO system is optimized by combining it with the elite sorting algorithm. During each iteration, not only the contemporary optimal paths are considered, but also the worst paths and average paths during this iteration are fully utilized for information exchange. The worst path provides information about the search space boundary, while the average path provides global information. By fully utilizing the internal information of the colony, the ants are better guided to find the global optimal solution during the search process.

The expression of the update strategy for the local pheromone is:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \rho\sum_{\varphi=1}^{\sigma}\Delta\tau_{ij}^{\varphi}(t) \tag{13}$$

$$\Delta\tau_{ij}^{\varphi}(t)=\begin{cases}\dfrac{N}{N_{\max}}\sigma(L_{\min}^{-1}-L_{\max}^{-1}),(i,j)\in D_s\\ \dfrac{N}{N_{\max}}\sigma(L^{-1}-L_{ave}^{-1}),(i,j)\in D_j\end{cases} \tag{14}$$

where: ρ is the adjustable parameter; σ is the number of elite ants; $L_{\min}$ is the length corresponding to the best path in each generation; L_{max} is the average length of the ants' paths in each generation; L_{max} is the current number of iterations; $N_{\max}$ is the maximum number of iterations; D_n is the optimal path in the contemporary period; D_j is the set of better paths in the contemporary period; and L is the length corresponding to the better path in each generation.

In the global pheromone updating strategy, the ACS pheromone updating strategy is introduced, which is based on Eq. (11). Namely

$$\tau_{ij}(t+1)=(1-\alpha)\tau_{ij}(t)+\alpha\sum_{k=1}^{\sigma}\Delta\tau_{ij}^{k}(t) \tag{15}$$

In Eq. (15): α is the global pheromone volatilization coefficient; $\Delta\tau_{ij}^{k}(t)$ is the amount of pheromone update on the corresponding path of the globally optimal ant, and the expression is:

$$\Delta\tau_{ij}^{k}(t)=\begin{cases}\dfrac{1}{L_e} & (i,j)\in D_e\\ 0 & \text{other}\end{cases} \tag{16}$$

In Eq. (16): L_e is the length of the globally optimal path searched from the start of path planning to the current search; D_c is the set of globally optimal paths. The improved algorithm will rank the paths based on their combined information. Since the top ranked ants are more likely to find shorter and better paths, more pheromones will be updated for the path trajectories they traveled.

3.4. Process for improving the ACO algorithm

The improved algorithm in this paper, as a heuristic search algorithm, can generate a higher-quality solution in a relatively acceptable time when dealing with large-scale, nonlinear and complex college students' career choice path planning problems due to its parallelism and distributed computing features. The process of the improved ant colony algorithm is as follows.

1) Construct a raster environment map through the actual environment, set the starting point and target point, and initialize the parameter assignment.

2) Calculate the initial value of the initial pheromone of the raster map according to Eq. 5).

3) Place the ants at the starting point of the raster map, calculate the heuristic function according to Eq. 7) and start the path search.

4) Calculate the transfer probability according to the ant colony system algorithm to determine the ant's next raster position.

5) Determine whether the ant arrives at the set target point, if so, continue to execute 6), otherwise return to 3) and enter the next cycle.

6) Update the pheromone as well as record the indicators according to Eq. 9) and Eq. 11).

7) Determine whether the iteration is completed, if so, output the optimal path, otherwise continue to execute 3).

4. Experiments on the performance of the improved ant colony algorithm

In this section, we will verify the performance of the improved ant colony algorithm based on Sigmoid statistical iteration proposed in this paper after improving the traditional ant colony algorithm, and explore the effectiveness of the career choice path planning model constructed in this paper.

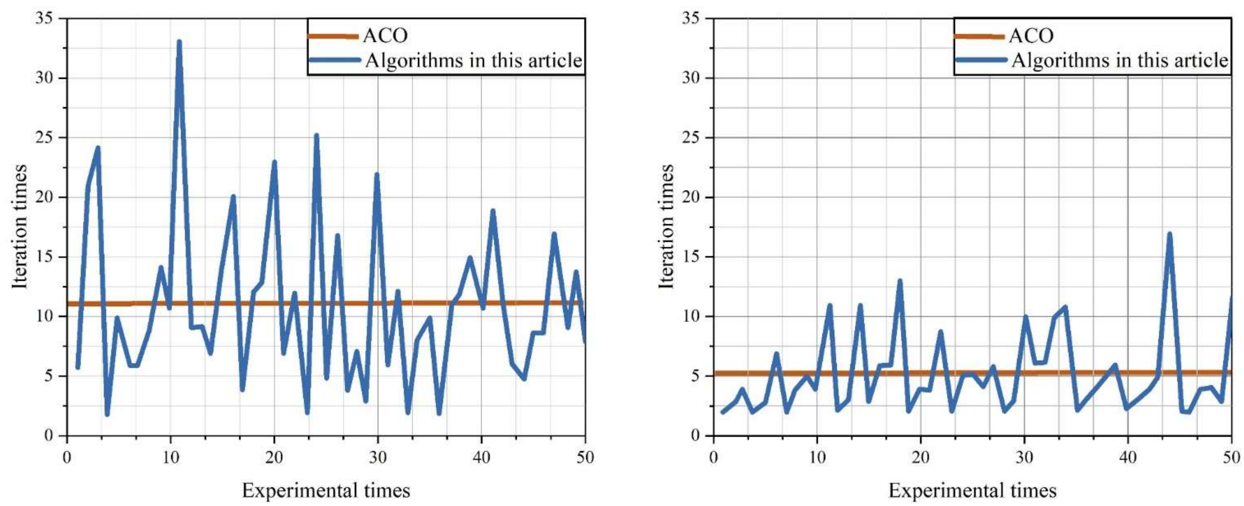
4.1. Stability experiments

The traditional ant colony algorithm (ACO) is chosen as a comparison, and the ACO algorithm and the improved ant colony algorithm based on Sigmoid statistical iteration proposed in this paper are run repeatedly for 50 times to compare the algorithm performance in terms of the optimal number of stable iterations, the worst number of stable iterations and the average number of iterations. The test results are specifically shown in Table 1. Observation of the data comparison can be found that the number of stable iterations of this paper's algorithm has been significantly reduced. The worst stable iteration number and the average iteration number of this paper's algorithm are 18 and 5.06, respectively, which is a decrease of 16 and 6.09 compared with the ACO algorithm.

Table 1. Comparison of test results

Algorithm	Optimal number of stable iterations	Worst stable number of iterations	Average number of iterations
ACO	2	32	11.15
Algorithms in this article	2	14	5.06

The stable iteration performance of the ACO algorithm and the algorithm in this paper is visualized, as shown in Figure 1. It can be seen that with the increase of the number of experiments, the number of stable iterations of the ACO algorithm also shows obvious fluctuations, and the number of stable iterations can be up to 33 times, while the lowest is only 1 time, with a large fluctuation amplitude. In contrast, the stabilizing iteration number of this paper's algorithm fluctuates less, and the stabilizing iteration number fluctuates in the interval of [1,14] in the 50 experiments of repeated runs. Overall, the algorithm in this paper significantly improves the stability of the algorithm and the ability of global optimization search, ensures the quality of understanding, and is able to provide college students with high-quality employment and entrepreneurship career choice planning paths.



(a)ACO (b)Algorithms in this article

Fig. 1. Stability comparison diagram

4.2. Environmental Simulation Experiment

In order to further prove the feasibility and effectiveness of the improved ant colony algorithm based on Sigmoid statistical iteration proposed in this paper in the face of complex and diversified college students' demand for career planning paths, this section carries out environmental simulation experiments on MATLAB 2022 for the algorithm of this paper. This environmental simulation experiment is divided into two parts. The first part is to verify and analyze the planning trajectory of this algorithm in 20×20 small-scale grid environment and ants, and the second experiment is to further verify the efficiency of this algorithm in the optimization process in 30×30 simulation environment. The comparison algorithms selected for this environment simulation experiment are ACO algorithm, IACO algorithm, TDI-MSACO algorithm.

4.2.1. 20×20 simulation environment. The experimental data of this paper's algorithm and ACO algorithm, IACO algorithm, and TDI-MSACO algorithm in the 20×20 simulation environment are specifically shown in Table 2. It can be seen that the ACO algorithm, IACO algorithm, and TDI-MSACO algorithm have performed 40, 25, and 16 iterations respectively, and the running time is 7.72 s, 2.86 s, and 3.24 s. In terms of the number of nodes, the ACO algorithm and the IACO algorithm have similar numbers of nodes, which are 30 and 31 respectively, while the number of nodes of the TDI-MSACO algorithm is significantly reduced with 16. Compared with the ACO algorithm, IACO algorithm, and TDI-MSACO algorithm, this paper's algorithm has the least number of iterations among all the algorithms, with only 5 iterations, and it has a short running time, which took only 1.07s, and the number of nodes is only 8. Obviously, the algorithm in this paper has excellent running efficiency.

Table 2. Comparison of 20×20 grid simulation results

Environmental scale	Algorithm	Iteration times	Nobe number	Running time(s)
20×20	ACO	40	31	7.72
	IACO	25	32	2.86
	TDI-MSACO	16	18	3.24
	Algorithms in this article	5	8	1.07

The convergence curves of this paper's algorithm with ACO algorithm, IACO algorithm, and TDI-MSACO algorithm in 20×20 simulation environment are specifically shown in Fig. 2. From the figure, we see that ACO algorithm and IACO algorithm realize the convergence at 42 and 21 respectively, and the optimal path length is 35.12 m and 32.13 m. TDI-MSACO algorithm and this paper algorithm converge significantly faster than ACO algorithm and IACO algorithm, and realize the convergence at 14 and 6 respectively; however, the final optimal path length of this paper algorithm is 2.14 m shorter than that of TDI-MSACO algorithm, which is 29.09 m. The convergence curves are shown in Fig. 2. MSACO algorithm by 2.14m to 29.09m, which is slightly better than TDI-MSACO algorithm in terms of optimization searching effect. Overall, the algorithm in this paper outperforms other comparative algorithms, and shows high stability and efficiency in terms of optimization effect and computation time, and is able to better cope with the multi-objective dynamic planning path demand of college students' career planning with huge data in colleges and universities.

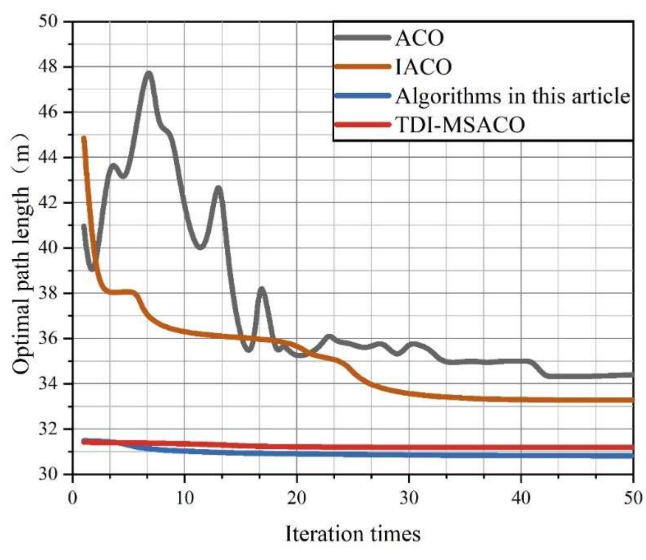


Fig. 2. Comparison of 20×20 grid algorithm convergence curve results

4.2.2. 30×30 simulation environment. To further verify the performance of the improved ACO algorithm based on Sigmoid statistical iteration proposed in this paper, a 30×30 scale simulation environment with higher environmental complexity is selected. The simulation experimental data of this paper's algorithm and ACO algorithm, IACO algorithm and TDI-MSACO algorithm in 30×30 simulation environment are specifically shown in Table 3. The shortest paths found by this algorithm, ACO, IACO and TDI-MSACO in 30×30 simulation environment are 46.18m, 60.36m, 51.62m and 47.5m respectively, and the number of iterations are 8, 54, 46 and 24 respectively, and the running time required to achieve smooth iteration is 4.56s, 18.87s, 13.28s and 8.12s respectively. In comparison, the IACO algorithm is slightly better than the ACO algorithm, and the TDI-MSACO algorithm shows a greater advantage, not only in the optimization effect, but also in the running time, but the algorithm in this paper has a lot of improvement compared with the TDI-MSACO algorithm.

Table 3. Comparison of 30×30 grid simulation results

Environmental scale	Algorithm	Optimal path length	iteration times	Nobe number	Running time(s)
30×30	ACO	60.36	34	54	18.87
	IACO	51.62	30	46	13.28
	TDI-MSACO	47.5	15	24	8.12
	Algorithms in this article	46.18	8	12	4.56

In summary, with the increasing complexity of the simulation environment, the improved ant colony algorithm based on Sigmoid statistical iteration proposed in this paper not only exhibits high stability, but also shows significant advantages in terms of solution quality compared with the comparison algorithm, which can provide university students with multi-objective dynamic employment and entrepreneurship career choice planning paths, and provide references for the employment and entrepreneurship direction recommendation for school students. It can provide university students with multi-objective dynamic employment and entrepreneurship career choice planning paths, provide reference for recommending the direction of employment and entrepreneurship for school students, and to a certain extent effectively promote the accurate employment and entrepreneurship of university students.

5. Career Choice Planning Path Recommendation System Based on Improved Ant Colony Algorithm

The traditional mode of career choice planning path recommendation based on search engine can no longer meet the needs of college students, and it is necessary to start from the multi-objective dynamic planning path model of college students' career choice proposed in this paper to improve the accuracy of career choice planning path recommendation. In this chapter, the improved ant colony algorithm proposed above is integrated to design and realize the career choice planning path recommendation system based on the improved ant colony.

5.1. Overall Architecture Design

1) Information Service Strategy Layer. Strategy layer is the core of the whole architecture, mainly responsible for analyzing and calculating each business, on the basis of improving ant colony algorithm, incorporating big data mining technology, integrating information collection, filtering, precision recommendation, and even intelligent search, employment prediction, etc., to form a complete and rigorous logical system.

2) Information service platform layer. The platform layer is an intermediate bridge between the system and the students and enterprise users, providing access and communication channels in a relatively open and shared state, managing the basic user information in the form of modules, and supporting the modification and editing of multi-dimensional information such as personal resume and skills assessment. The platform is also equipped with a search engine, so that students can input their job-

seeking wishes to seek target enterprises, and enterprises can search and browse graduates' public resume information, thus solving the problem of information asymmetry in the job market and enhancing the success rate of employment. All platform layer activities are within the scope of supervision and management, browsing, favorites and other behaviors are transmitted back to the database for recording and storing, laying the foundation for the next step of analysis and recommendation. At the same time, the administrator account can also be analyzed by big data to find anomalies, so as to eliminate fraudulent and false accounts and ensure the quality of employment and recruitment information.

3) Information Data Warehouse Layer. The data warehouse layer mainly plays the role of recording and storing functions, which can integrate and transform the job search and recruitment information of a large number of organizations, and provide the basis and support for the construction of the model. Here, MySQL technology is used, which is small in size, low in cost and open source code, which can better meet the economic demand. Most of the codes are written in C language and tested by various compilers, so the overall portability is good. It is also compatible with AIX, FreeBSD and other operating systems during actual operation. The optimized SQL algorithm creates conditions for query speed enhancement, and the multi-threaded operation logic improves the utilization of CPU resources and significantly reduces the difficulty of management, inspection and optimization.

5.2. User model construction and operation

User model is a data structure with descriptive and intuitive characteristics, which can objectively feedback the characteristics of user needs, interests, behaviors, etc., and provide the correct direction and ideas for the multi-objective dynamic planning path of college students' career choices, and its accuracy is the key to judge the degree of effectiveness of the system. In this design, the operation steps of the model are mainly divided into the following points.

1) Information collection, based on the network platform, collecting both explicit and implicit data.

2) Model creation, the service object also includes college students and enterprises, mainly through data cleaning, screening, and fixed algorithm operation, the formation of job-seeking user profiles and occupational demand model, the model building process combined with the weight setting method.

3) Extraction of ensembles, the main purpose of this step is to improve the efficiency of the search, the system is based on the created model, from which the ensembles composed of objective features, subjective interests, etc. are extracted, and the key attributes of the ensembles are assigned, stored in the core database, and the differentiated vector sets are generated.

4) Data processing, this step focuses on the use of improved ant colony algorithm, when college students enter the browsing, query session, the system will automatically extract their model vectors, and with the demand model vectors to match the degree of calculation, and ultimately in accordance with the weight of the recommendation degree to complete the sorting. The higher the similarity, the higher the ranking of the search results, thus better reflecting the collaborative filtering thinking.

5) A self-improvement mechanism is set up in the application link. When the system processes and calculates the student model, it may find individuals with high similarity, and mark them as "friends" in pairs, and the tendencies of other individuals in the set will be used as a reference when recommending, so as to facilitate the expansion of the recommendation range and the improvement of accuracy.

5.3. Service platform module design

The service platform adopts B/S architecture, students and enterprise users do not need to install and maintain the client, through the web page can be accessed by the platform, query operations, business expansion is simple and distributed characteristics are significant, the update link can be synchronized and optimized by changing the web page, while using MySQL database technology, the development is completed in Java, omitting the header files, pointers and other features, the overall more rigorous and concise. The module is divided into the following parts.

1) User Login Module. The design of the login module is to better access to the behavioral dynamics of students, enterprises and other subjects, thus laying the foundation for implicit information collection and employment information recommendation.

2) Graduate Recommendation Module. Graduate recommendation module can provide a channel for personal information management, which can visually present graduates' names, genders, contact information, etc. When there are changes in the information, graduates can conveniently change it through this module, and at the same time, it is equipped with the functions of setting up career choice planning path recommendation and database management.

3) Service Interface Module. When graduates use it, they only need to open the interface through the recommendation service module to use the service, and the protocol adopts the HTTP form. The module can realize more functions, such as closing the recommendation system and opening the recommendation system. When the module normal operation in the event of an accident or configuration is modified, you can also restart the recommendation service to achieve the purpose of initializing the recommendation engine parameters, but also supports non-logged-in user recommendation services and user behavior monitoring feedback and other functions.

4) Administrator and Employer Module. The administrator module contains three aspects, the first is user management, the system internally designated admin account, has the highest authority and can manage all students, employers account, to modify, blocking operations, to prevent the inflow of false accounts; the second is the information management, that is, the administrator has the right to view, delete the information of all parties; finally, the database management, support password reset function. The employer module is mainly set up with two functions: information management and graduate search. The former is used to publish recruitment information, which can be changed and edited in real time on the basis of account password login, and the objects include recruitment title, category, number of people, etc. The latter allows access to the information of graduates, which helps to improve the efficiency of employment information interaction.

6. Application Practice of Career Choice Planning Path Recommendation System

Testing the career choice planning path recommendation system constructed in this paper and carrying out application practice help to ensure the effectiveness and fairness of the system, verify the performance of the system in this paper, and explore whether it can satisfy the multi-objective dynamic planning needs of college students' career choice.

6.1. System performance testing

The performance testing of the career choice planning path recommendation system aims to evaluate the performance of the system under specific conditions, focusing on checking the performance of the system under different load levels, number of concurrent users or resource utilization. Through system performance testing, potential performance bottlenecks can be identified, system design can be improved, and code can be optimized to ensure that the system can run efficiently in actual use and provide good user experience.

6.1.1. Web stress testing. Response time is the main indicator to measure the response speed of the platform, the time from the user request to the completion of the platform response, the response time is short to enhance the user experience and enhance user satisfaction. Concurrency is the main indicator to measure the concurrent processing capability of the platform, the larger the concurrency, the more requests can be processed at the same time; CPU utilization is the main indicator to measure the load and resource utilization of the platform, the high CPU utilization of the platform may lead to an increase in response time, throughput reduction and other performance problems. Therefore, we combine the response time with the concurrency to test the response time of the system at the highest concurrency or maximum load, and test the bottleneck of the system performance to facilitate the subsequent optimization of the system. Postman software is used to stress test the system web pages to obtain their average response time and pass rate to evaluate the performance of the platform, the stress test results of the system web pages are shown in Table 4. According to the stress test results in the table, when the concurrency scale (number of users) is 1000, the average response time of the platform home page is 322ms and the maximum response time of 90% is 393ms, the throughput is 394, and the pass rate is 100%, which indicates that the system in this paper has a good performance in terms of concurrency.

Table 4. System web page stress testing

Concurrency scale	Average response time (ms)	90 % maximum response time (ms)	Throughput (TPS)	Pass rate (%)
50	206	265	485	100%
100	218	282	477	100%
300	237	325	450	100%
500	305	382	425	100%
1000	322	393	394	100%

6.1.2. System resource utilization test. In this section, we test the server resource utilization of the system in this paper under different concurrency sizes. The server resource utilization is presented by two indicators: CPU occupancy rate and memory occupancy rate. The server resource utilization of this system is compared with that of the traditional career choice planning path recommendation system based on collaborative filtering algorithm (referred to as “traditional system”), as shown in Table 5. The resource utilization of both this system and the traditional system grows with the increase of concurrency scale. When the number of users reaches 1,000, the CPU and memory utilization rates of both this system and the traditional system drop to the lowest, but the CPU and memory utilization rates of this system are 51.94% and 54.31%, which are 35.32% and 39.83% lower than those of the traditional system. Meanwhile, in other concurrency scale cases, the CPU and memory utilization of this paper's system are always lower than that of the traditional system.

Table 5. The resource occupancy rate of the system

Concurrency scale	System of this article		Traditional system	
	CPU occupancy rate(%)	Memory occupancy(%)	CPU occupancy rate(%)	Memory occupancy(%)
50	36.47	38.68	68.61	71.85
100	40.16	42.11	77.83	80.51
300	45.37	48.99	88.61	90.48
500	51.94	54.31	98.15	97.25
1000	64.68	60.17	100	100

6.2. Evaluation of system functions

The functional test of the career choice planning path recommendation system is to ensure the effectiveness and stability of the system's core function of career choice planning path recommendation. The data used in this section of the experiment comes from the employment information data of graduates of a university from 2020 to 2023, and the amount of data after data preprocessing is 153713.

6.2.1. Recommendation accuracy evaluation. In order to more intuitively see the effectiveness of the career choice planning path recommendation function of the system in this paper, this section uses the test dataset to generate a confusion matrix heat map, which more intuitively shows the accuracy of the recommendation results for each sample in the dataset. The generated confusion matrix heat map is shown in Figure 3. The color shades and the size of the numbers in the cells show that most of the samples are concentrated in the cells on the diagonal, and only a few samples are distributed outside the diagonal, which proves that most of the career choice planning path recommendations made by the data are consistent with the actual direction of employment and entrepreneurship career choices, and that the accuracy of the recommendations is better.

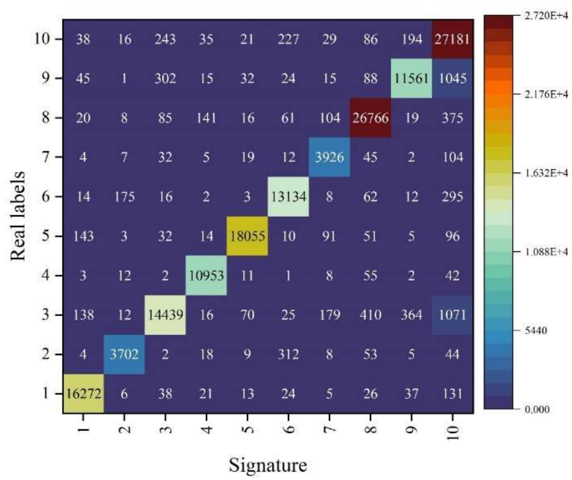


Fig. 3. Confusion matrix heat map based on probability

6.2.2. Evaluation of the quality of recommendations. In this section, the employment quality index will be introduced as a recommendation quality evaluation index to measure the recommendation quality of the system in this paper for career choice planning path recommendation. The range of the employment quality index is set to [0.0,10.0], and the step size is 0.5. The higher the value of the employment quality index, the better the quality, and vice versa, the worse the quality. Still choosing the traditional system as the object of comparison, we obtain the employment quality index of 10 college majors (represented by 1~10 in order), such as computer, business administration, finance, civil engineering, chemical engineering, art design, accounting, Chinese language and literature, communication, psychology, etc., in the data used for the experiment, which is specifically shown in Fig. 4. It can be clearly seen that the employment quality index of this paper's system is higher than that of the traditional system in all majors, and the difference between the two employment quality indexes can reach up to 6.93. Obviously, the career choice planning path recommendation system based on the improved ant colony algorithm constructed in this paper can provide students with career choice planning path recommendations in a more scientific and reasonable way.

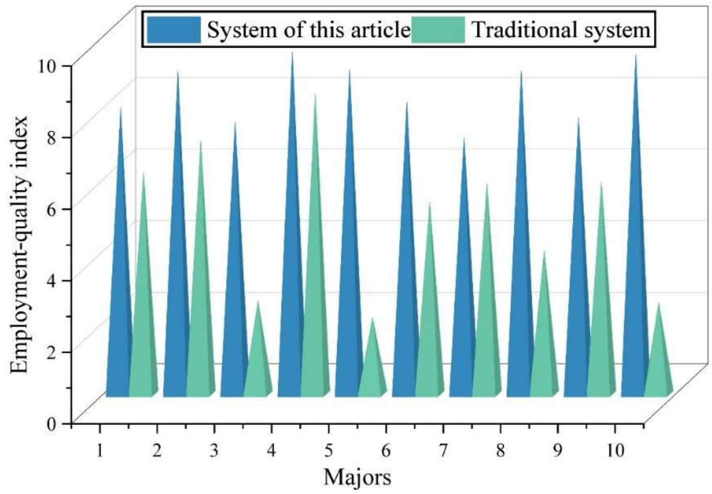


Fig. 4. Comparison of employment quality index

7. Conclusion

In this paper, starting from the shortcomings of the traditional ACO algorithm, an improved ACO based on Sigmoid statistical iteration is proposed to construct a career choice path planning model, which is used as the basis of functional implementation to design and construct a career choice planning path recommendation system based on the improved ACO algorithm.

In the performance test of this paper's improved ACO algorithm, the worst stable iteration number and the average iteration number of this paper's algorithm are 18 and 5.06, respectively, which are 16 and 6.09 lower than that of the traditional ACO algorithm and the stable iteration number fluctuates stably in the interval of [1,14]. Obviously, the stability of the algorithm in this paper is significantly better than that of the ACO algorithm. Further environment simulation experiments are carried out to verify the effectiveness of the improved ACO algorithm in this paper. In the 20×20 simulation environment, the number of iterations and the number of nodes of this paper's algorithm are less than those of the ACO algorithm, IACO algorithm, and TDI-MSACO algorithm which are used as comparisons, which are 5 and 8, respectively. In addition, this paper's algorithm also has the shortest running time, which takes only 1.07 s in the experiment, and the optimal path length is the least 29.09 m. In the 30×30 simulation environment, the optimal path length, iteration number, and running time of this paper's algorithm reaches 46.18 m, 8 iterations, and 4.56 s, which is also the best performance among all algorithms. Overall, the improved ACO algorithm based on Sigmoid statistical iteration proposed in this paper has significant advantages in terms of solution quality while possessing very high stability.

To test the effectiveness of the career choice planning path recommendation system constructed in this paper and carry out the application practice. In the performance test of the system, when the number of users reaches up to 1,000, the average response time and 90% of the maximum response time of the system in this paper are 322ms and 393ms, respectively, and the pass rate reaches 100%, which has a good performance in terms of concurrency.The CPU occupancy rate and the memory occupancy rate reaches 51.94% and 54.31%, which is lower than that of the traditional system by 35.32%, 39.83%, respectively, 39.83% lower than the traditional system. Using the test dataset to generate a heat map of the confusion matrix, most of the samples are concentrated on the diagonal cells, and the accuracy of the career choice planning path recommendation is good. In any major in the experimental data, the employment quality index of this paper's system is always higher than that of the traditional algorithm, which can provide students with scientific and reasonable career choice planning path recommendation.

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