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An Improved Ant Colony Optimization Algorithm for Recommendation of Micro-learning Path

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***Abstract*—This paper proposes an approach of recommending micro-learning path based on improved ant colony optimization algorithm. Micro-learning is a new learning style, which can be used to support learning in short time because of its micro-learning units. Each micro-learning unit consists of a small knowledge unit that can be learned at fragmented time. Meanwhile, micro-learning is more flexible than other learning styles in organizing or reorganizing learning path according to the transition of learner. In order to improve learning efficiency, a suitable learning path contained a sequence of micro-learning units is recommended to learner, which is optimized according to his/her transition. During the process of micro-learning, the proposed algorithm can detect learner's learning transitions of knowledge level, knowledge area and learning goal according to the operation of learner. In this study, the premature problem of ant colony algorithm is solved by optimizing the mechanism of initialization and update of pheromone. The experimental results show that the algorithm has high efficiency in micro-learning path recommendation.**

***Index Terms*—Ant colony optimization, learning path, micro -learning**

I. INTRODUCTION

Micro-learning is a new style of e-learning, which was presented in 2005 firstly [1]. A lot of attention had been paid by Chinese researchers to micro-learning since 2008. The main feature of micro-learning is its short or small learning unit. Micro-learning deals with relatively small learning units and short-term learning activities [2]. Therefore, learners can use fragmented time in learning rather than a long time. That is to say, learners can learn in any free time at anywhere even if a fragmented time.

A series of learning units constitutes a learning path, which can help learners to achieve their learning goals effectively [3]. The micro-learning units can be organized flexibly, because it is more micro than the unit of other learning style. According to individual differences of learners and correlations among micro-learning units and learners, we expect that a series of suitable micro-learning units can be extracted, and a series of suitable learning paths can be organized for target learners to improve their learning efficiency.

The self-study is a feature of ant colony algorithm, which can be used to improve the efficiency of recommending micro-learning path. In this study, according to the level and specific area of knowledge, various learning goals are extracted from some open learning resources of MOOC sites, which consist of a series of learning units respectively. In details, the learning units are divided into three levels of ease, normal and difficulty, and the learners are divided into three levels of beginning, intermediate and senior correspondingly. During the learning process, the learning statuses of learners are assessed by their test results, and then, the suitable learning goals are extracted in order to adapt to the transition of test results. Furthermore, the learning paths are recommended to learners based on the extracted learning goals.

Therefore, we propose an improved ant colony algorithm to enhance the efficiency of learning by recommending the suitable micro-learning path according to the learner's learning status. The paper is organized as follows. Section I is introduction, the study significance and layout are clarified. Section II introduces the related work of this study. The basic concepts and definitions are explained in Section III. The modules of the algorithm are described in Section IV. The results of experiments are presented in Section V. Finally, we give the guidelines for future work in Section VI.

II. RELATED WORK

The algorithms of recommending learning path are focused in personalized learning [4]. In this study field, Brusilovsky et al. proposed an algorithm that recommended learning path according to the knowledge level and learning goal [5]. Many researches tried to optimize the algorithm based on the research of Brusilovsky et al. Chen proposed an algorithm that recommended learning path according to the difficulty of learning object and the knowledge level of learners [6]. Chen built a learning object model based on Item Response Theory, which simplified the descriptions of learning objects. Chang et al., Berg et al. and Yang et al. proposed some algorithms respectively, in which, some learning style recognition methods are used to recommend learning path [7-9]. Chen proposed an improved ant-colony algorithm to optimize the classification of learning style furthermore [10].

Micro-learning is a new learning style of E-learning, which has gained a rapid growth. In recent year, the research of micro-learning was extends into two fields, the theoretical

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study and the applied study.

In the field of theoretical study, many researchers tried to build the theory foundation of micro-learning. Some researches take e-learning, distance education and ubiquitous learning as a starting point. However, the mature system of theoretical structure has not established up to now [11, 12].

In the field of applied study, the learning model and instructional design of micro-learning are popular topics. Some researchers built their micro-learning environment based on social networking platform, in which, the learning resource can be accessed by mobile devices [13, 14]. The other researchers tried to improve learning efficiency by applying some classical theories and methods to the micro-learning [15, 16].

Based on the above researches, our proposal combines the features of micro-learning with recommending personalized micro-learning path. The improved algorithm can detect learning status of learner at real-time, and recommend them suitable learning path in order to adapt the transitions of them.

III. CONCEPTION AND DEFINITION

Some conceptions and definitions related to our proposal are described in this section.

A. *Conception and Definition Related to Learner*

The knowledge area, knowledge level and learning goal of learners are taken into consideration.

- **Knowledge area** - The learner's knowledge area is determined according to the interests of learner. The micro-learning units belonged to the learner's knowledge area will be used to organize the micro-learning paths for the target learner.
- **Knowledge level** - The learner's knowledge level are assessed according to the corresponding knowledge areas of learner.
- **Learning goal** - The learner's learning goal is inferred according to the knowledge areas and levels of learner.
- **Learning status -** The learner's learning status is used to describe the current learning situation of target learners.

Learners' knowledge areas and their corresponding knowledge levels are important factors. The knowledge areas can be chosen by learners, and then, the test learning units are set to confirm the knowledge levels of learners in the knowledge areas.

The vector $S_o = \{S_o^1, S_o^2, S_o^3 \ldots S_o^i \ldots S_o^n\}$ denotes the knowledge areas that learner S_o is interested in, and *n* is the total number of knowledge areas. If a target learner is interested in the knowledge area *i*, then $\mathrm{S_o^i} = 1$, otherwise $\mathrm{S_o^i} = 0$. Each learner only can choose one knowledge area to learn at the same time.

On the condition of $S_o^i = 1$, the knowledge levels in the corresponding knowledge areas are described as follows. There are three knowledge levels. $\mathrm{A_o^i} = 1$ denotes that the learner S_o is a beginner, and he/she has little knowledge in the area *i*; $\mathrm{A_o^i} = 2$ denotes that the learner S_o is an intermediate learner, and he/she has basic knowledge in the area *i*; $\mathrm{A_o^i} = 3$ denotes that the learner S_o is a senior learner, and he/she has high level in the area *i*.

The learners' knowledge levels can be assessed by the scores of test learning units in the corresponding knowledge area.

The learning goals of learners are inferred according to their knowledge levels respectively. For a target leaner, if $\mathrm{A_o^i} = 1$, his/her learning goal is regarded as getting basic knowledge in area *i*; if $\mathrm{A_o^i} = 2$, his/her learning goal is regarded as getting intermediate knowledge in area *i*; if $\mathrm{A_o^i} = 3$, his/her learning goal is regarded as getting advanced knowledge in area *i*.

The learning statuses are defined as six types: stationary status, active status, change status, degradation status, up-gradation status, and initial status. The details of these status will be introduced in Section IV.

B. *Conception and Definition Related to Micro-learning*

The micro-learning unit is the basic unit in learning activity, which can be used for learning and finished in a short time. In this study, the knowledge area and the knowledge level are two important features of micro-learning unit.

The micro-learning units are divided into several clusters according to knowledge areas. Furthermore, the micro-learning units are divided into three levels according to the difficultly of knowledge. The knowledge areas and levels of micro-learning units are determined by provider of learning resource.

The vector $L_m = \{L_m^1, L_m^2, L_m^3 \ldots L_m^i \ldots L_m^n\}$ denotes the knowledge areas, where *n* is the total number of knowledge areas. If a micro-learning unit L_m belongs to the area *i*, then $L_m^i = 1$; otherwise $L_m^i = 0$. We assume one micro-learning unit only belongs to one knowledge area.

In this study, we assume there are three knowledge levels. $C_m^i = 1$ denotes the micro-learning unit L_m has some basic knowledge in the area *i*, and its knowledge level is ease; $C_m^i = 2$ denotes the micro-learning unit L_m contains the medium difficulty knowledge in the area *i*, and its knowledge level is normal; $C_m^i = 3$ denotes the micro-learning unit L_m contains the higher difficulty knowledge in the area *i,* and its knowledge level is difficulty.

The learning path is a sequence of micro-learning units. There are two types of learning paths in this study. The first one is the standard learning paths called original learning paths, which are determined by the providers of learning resource. The second one is the personalized learning paths which are generated by the proposed algorithm dynamically according the transitions of learners in the learning process.

Directed graph$\mathrm{G}(L, D)$ is used to express the correlations of micro-learning units. In graph G, L denotes the set of micro-learning units; $\mathrm{D} = [d_{ij}]$ denotes the order matrix of micro-learning units; $d_{ij} = 1$ denotes the order of micro-learning unit L_i is in front of micro-learning unitL_j; otherwise the order of micro-learning unit L_i is behind micro-learning unit L_j.

IV. IMPROVED ANT COLONY ALGORITHM

A. The basic ant-colony algorithm

Ant colony algorithm is a classical algorithm of swarm intelligence, which is also a successful application of bionics in mathematics field. In details, ant colony algorithm has high parallelism, positive feedback and cooperativeness, which has been widely used in many fields, such as intelligent search and global optimization [17]. The TSP (Traveling Salesman Problem) is a typical case of ant colony algorithm, which is explained as follows.

The TSP answers the following question. Given a list of cities and the distances between each pair of cities. And then, calculating the shortest possible route that a traveler visits each city exactly once and returns to original city [18]. The process of TSP based on ant colony algorithm is shown as follows.

Step 1: Initializing the parameters of algorithm;

Step 2: Judging the access status of ant: if there is no any ant visited any one city, put an ant in a city randomly. Otherwise, choosing the next city according to Formula (1);

Step 3: Updating the pheromone concentration according to Formula (2);

Step 4: Judging whether the solution meets the condition (maximum number of iterations), If it does not meet the condition, the number of iterations plus one, go to step 2, otherwise, recording the current optimal solution;

Step 5: Outputting the optimal solution.

The mentioned formula is shown as follows.

$$P_{ij}^k(t) = \begin{cases} \frac{[\tau_{ij}(t)]^\alpha \times [\eta_{ij}(t)]^\beta}{\sum_{s \in T_k} [\tau_{is}(t)]^\alpha \times [\eta_{is}(t)]^\beta}, & if (j \in T_k) \\ 0, & if (j \notin T_k) \end{cases} \quad (1)$$

where,$P_{ij}^k(t)$ denotes the probability of an ant choose the way of from city i to city j at the time t; $\eta_{ij}(t)$ denotes the heuristic information between city i and city j at the time t; $\tau_{ij}(t)$ denotes the pheromone concentration from city i to city j at the time t; α and β are the parameters which are used to control the influence of pheromone concentration and heuristic information respectively; T_k denotes the data set of cities which the ant k haven't visited at the time t. In details, $\eta_{ij}(t)$ is a prior knowledge, which is expressed as a reciprocal of distance between city i and city j.

$$\tau_{ij}(t+1) = (1-\rho) \times \tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^k(t) \quad (2)$$

Formula (2) expresses the transition of pheromone concentration, in which, there are m ants move from city i to city j in the time from t to $(t + 1)$. In details, $\Delta\tau_{ij}^k(t)$ denotes the pheromone concentration retained by ant k in the path $(i \rightarrow j)$ at the time $(t + 1)$; ρ denotes the evaporation coefficient of pheromone.

The conclusion shows that the number of ants can affect the pheromone concentration, that is to say, for a target path $(i \rightarrow j)$, if there are more ants through the path, the pheromone concentration will rise.

B. Process of the improved algorithm

The improved algorithm recommends the micro-learning units for the target learner based on the ant-colony algorithm. The recommendation rule of micro-learning units is improved by decided selection with random selection.

The process of recommending is shown as follows.

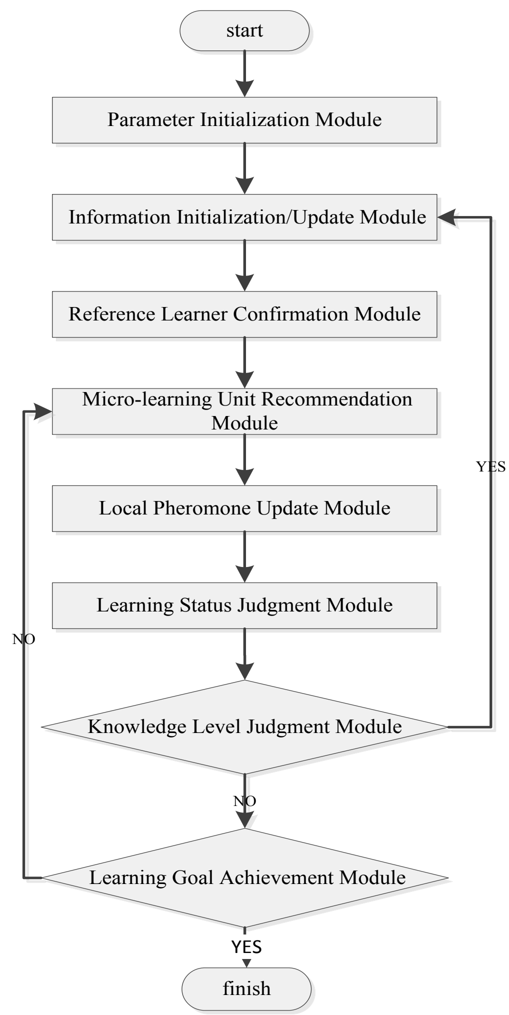

Figure 1 The flow chart of improved Ant colony algorithm

Step 1: Parameter Initialization Module: This module is used to initialize the parameters and pheromone concentration of new micro-learning unit in the proposed algorithm.

Step 2: Information Initialization/Update Module: This module is used to initialize or update the basic data set of learner, knowledge area, knowledge level and learning goal;

Step 3: Reference Learner Confirmation Module: This module is used to confirm the reference learners who are similar to target learner;

Step 4: Micro-learning Unit Recommendation Module: This module is used to recommend micro-learning unit to target learner according to his/her learning status;

Step 5: Local Pheromone Update Module: This module is used to update the local pheromone;

Step 6: Learning Status Judgment Module: This module is used to judge the learning status of target learner.

Step 7: Knowledge Level Judgment Module: This module is used to judge the knowledge level of target learner according to his/her transition. If there is any transition of target learner, the process will jump to Information Initialization/Update Module, and the data set of target learner will be updated;

Step 8: Learning Goal Reached Achievement Module: This module is used to judge a target learner whether he/she reaches his/her study goal. If the target learner does not reach, the process will jump to step 4; otherwise, the learning of current learning path is finished.

C. *Module of the improved algorithm*

1) *Parameter Initialization Module*

This module is responsible for the preparation work of the improved algorithm. Firstly, the initial value of the parameters in the proposed ant-colony algorithm will be given. Then, the value of α, β and ρ will be identified, in which α and β are the parameters which are used to control the influence of pheromone concentration and heuristic information respectively, and ρ denotes the evaporation coefficient of pheromone.

Secondly, the pheromone of new micro-learning units is initialized by this module, according to the correlation between micro-learning units and the pheromone distribution of existing micro-learning units. For new micro-learning unit L_k, pheromone concentration τ_{ks}(t) between L_k and existing micro-learning unit L_s at current time *t* is described in Formula (3).

$$\tau_{ks}(t) = \vartheta_1\left(w_{ki} \times \tau_{is}(t)\right) + \vartheta_2 w_{ks} \tag{3}$$

Where, w_{ki} is the similarity between L_k and L_i; L_i is the micro-learning unit in the system expect L_k and L_s . w_{ks} denotes the similarity between L_k and L_s ; $\tau_{is}(t)$ is the pheromone concentration between L_i and L_s at time *t*; ϑ_1 and ϑ_2 are the weight factor.

2) *Information Initialization/Update Module*

This module is mainly responsible for the initialization and updating the information of learner. Firstly, the basic characteristics of new learners are unknown. Therefore, the new learners need to choose their knowledge area according to interest. Secondly, the new learners need to finish a level test learning units in order to confirm their knowledge level. Finally, the learning goals are inferred according to the knowledge level of learner respectively. Formula (4) is used to describe this process.

$$A_o^i = \begin{cases} 1 & T_{low} < 60 \\ 2 & T_{middle} < 60 \\ 3 & T_{high} < 60 \end{cases} \tag{4}$$

Where, T_{low}, T_{middle} and T_{high} are the scores ordered by the difficulty of test learning units; A_o^i is the knowledge level of learner S_o in the knowledge area *i*.

The above is used to confirm which knowledge levels would suit learners. If a learner chooses a test learning unit of easy level, and the test result T_{low} is lower than 60, the knowledge level of ease will be recommended to him/her. Otherwise, the learner will be required to finish the test learning unit of normal level. If the result T_{middle} is lower than 60, the knowledge level of normal will be recommended to him/her. Otherwise, the learner will be required to finish the test learning unit of difficult level. If the result T_{high} is lower than 60, the knowledge level of difficulty will be recommended to him/her. Otherwise, the learner does not need to learn the chosen learning contents. In the whole learning process, the knowledge levels and goals of target learners will be inferred according to their transition of learners' learning status.

If the knowledge level of learner is changed, the learning goal of target learner will be changed with this transition. If the current learning status is degradation status which means the knowledge level of target learner was overvalued, the determined knowledge level of target learner will be changed to the lower level in the corresponding knowledge area. If the current learning status of learner is up-gradation status which means the knowledge level of target learner was undervalued, the determined knowledge level of target learner will be changed to the high level in the corresponding knowledge area. At the same time, the learning goals will be adjusted synchronously.

3) *Reference Learner Confirmation Module*

The similarity of learners contains two aspects, the basic characteristics and the learning records. The correlation factor F_{kt} between learner S_k and S_t is set as Formula (5).

$$F_{kt} = \varepsilon_1\left(\left|S_k^i - S_t^i\right| + \left|A_k^i - A_t^i\right|\right) + \varepsilon_2\left(\left|T_k^j - T_t^j\right|\right) \tag{5}$$

where S_k^i and S_t^i are the knowledge area of learner S_k and S_t; A_k^i and A_t^i are the knowledge level of S_k and S_t; T_k^j and T_t^j are the scores of learner S_k and S_t of the learning unit L_j; ε_1 and ε_2 are the weight factor. According to the test of algorithm, the learners who have high similarity with target learners will be regarded as the reference learners of target learner.

4) *Micro-learning Unit Recommendation Module*

This module is used to recommend learning units according to the transitions of target learners. We assume learner S_o who finished micro-learning unit L_i just now, and the current original learning path is *J*. The next micro-learning unit L_j will be recommended as the follows.

If the learning status of target leaner is stationary status which means the current learning path is suitable for target learner. The recommendation rule of micro-learning is in accordance with Formula (6).

$$p_{ij}^{S_o}(t) = \begin{cases} [\eta_{ij}]^{\alpha} \times [\tau_{ij}(t)]^{\beta} / \sum [\eta_{ij}]^{\alpha} \times [\tau_{ij}(t)]^{\beta}, & L_j \in P(J) \\ 0, & L_j \notin P(J) \end{cases} \quad (6)$$

where, α and β denote the influence factors of the heuristic information η_{ij} and pheromone concentration $\tau_{ij}(t)$ respectively; $P(J)$ denotes the next micro-learning unit L_j of current micro-learning unit L_i on the learning path *J*.

If the learning status of target learner is active status which means the current learning path is not a good match to the target learner. But the learning unit is suitable for the target learner. The recommendation rule of micro-learning is in accordance with Formula (7).

$$p_{ij}^{S_o}(t) = \begin{cases} [\eta_{ij}]^{\alpha} \times [\tau_{ij}(t)]^{\beta} / \sum [\eta_{ij}]^{\alpha} \times [\tau_{ij}(t)]^{\beta}, & L_j \in Q(J) \\ 0, & L_j \notin Q(J) \end{cases} \quad (7)$$

where, α and β denote the influence factors of the heuristic information η_{ij} and pheromone concentration $\tau_{ij}(t)$ respectively; $Q(J)$ denotes the micro-learning units on the learning paths which are similar to the current learning path.

If the current learning status of learner is change status which means the current micro-learning unit is not suitable for the target learner. The recommendation rule of micro-learning is in accordance with Formula (8).

If the learning status of target learner is degradation status or up-gradation status, which means the knowledge level of target learner was updated just now. The recommendation rule of micro-learning is in accordance with Formula (8).

$$p_{ij}^{S_o}(t) = \begin{cases} [\eta_{ij}]^{\alpha} \times [\tau_{ij}(t)]^{\beta} / \sum [\eta_{ij}]^{\alpha} \times [\tau_{ij}(t)]^{\beta}, & L_j \in P(S_o) \\ 0, & L_j \notin P(S_o) \end{cases} \quad (8)$$

where, α and β denote the influence factors of the heuristic information η_{ij} and pheromone concentration $\tau_{ij}(t)$ respectively; $P(S_o)$ denotes the micro-learning units which the learner S_o haven't learned yet.

If learning status of target learner is initial status. The recommendation rule of micro-learning is in accordance with Formula (9).

$$p_{j}^{S_o}(t) = \begin{cases} \lambda_{oj} / \sum \lambda_{oj}, & L_j \in T(S_o) \\ 0, & L_j \notin T(S_o) \end{cases} \quad (9)$$

where, λ_{oj} denotes the correlation between learner S_o and micro-learning unit L_j; $\mathrm{T}(S_o)$ denotes the micro-learning units which has learned by the reference learner of target learner S_o.

In the above formulas, one important factor is heuristic information. It plays an important role in the determination of the probability in the selection of micro-learning units.

In this algorithm, the heuristic information depends on two factors, the similarity between micro-learning units and the reference learners of target learners.

The similarity w_{mn} between L_m and L_n is depends on their attributes.

$$w_{mn} = \omega\theta_1 + (1-\omega)\theta_2 \quad (10)$$

where, θ_1 is determined by the knowledge level of learning unit, which can be calculated by Formula (11); θ_2 is determined by the learning path information, which can be calculated by Formula (12).

$$\theta_1 = 1 - \sum_{i=1}^{n} \left| C_m^i - C_n^i \right| \quad (11)$$

$$\theta_2 = \begin{cases} 1, & \text{if } \mathrm{E}(L_m, L_n) = 1 \\ 0, & \text{if } \mathrm{E}(L_m, L_n) = 0 \end{cases} \quad (12)$$

As shown in Formula (12), if L_m and L_n belong to the same original learning path, the value of $\mathrm{E}(L_m, L_n)$ is 1, otherwise is 0.

5) Local Pheromone Update Module

Local updating strategy is point to updating the pheromone concentration according to the test score while the learner finishing the study of one micro-learning unit. When the learner S_k finished learning path $L_i \rightarrow L_j$, the local updating strategy is expressed as Formula (13).

$$\tau_{ij}(t+1) = (1-\rho) \times \tau_{ij}(t) + \Delta\tau_{ij}^{k}(t) \quad (13)$$

Where, $\rho(0 \le \rho \le 1$ denotes evaporation coefficient of pheromone. $\Delta\tau_{ij}^{k}(t)$ denotes the test score of $L_i \rightarrow L_j$.

6) Learning Status Judgment Module

The learning status is to represent the learner's mastery of knowledge and the compatibility of the current learning path. The details are described as follows.

- **Stationary status** - If the test score is excellent, which indicates that the current learning path is suitable for the learner. The target learner will continue along the current learning path. The learning status of target learner is stationary status.
- **Active status** - If the test score is good or fair, which indicates that the current learning path is not suitable for the target learner. Then, the knowledge level will be changed and a suitable learning path will be recommended to the target learner. And the learning status of target learner is active status.
- **Change status** - If the test score is pass, which indicates the current micro-learning unit is not suitable for the target learner. Then, the recommended strategy will be adjusted. The learning status of target learner is change status.
- **Degradation status** - If the test score is fail, which indicates the knowledge level of the current micro-learning units is not suitable for the target learner. The learning status of target learner is degradation status.
- **Up-gradation status** - If the comprehensive test scores of three successive learning paths are excellent which indicates the knowledge level of current

micro-learning units is not suitable for the target learner. The learning status of target learner is up-gradation status.

- **Initial status** - The learner participates in learning for the first time or starts a new learning path. The learning status of target learner is initial status.

7) Knowledge Level Judgment Module

If the current learning status is degradation status or up-gradation status, the knowledge level of learner will be changed, and the judgment of information of learner needed needs to amend renew.

8) Learning Goal Achievement Module

The final test result of each micro-learning unit is used to confirm whether a target learner reaches the learning goal. If the target learner finished 90% of micro-learning units in the current original learning path, and the test results achieved good level (excellent, good, medium and poor, the four levels in all), that means the target learner achieved the learning goal. In the other case, if the target learner finished all micro-learning units in the current learning path, which also means the target learner achieved the learning goal. At the same time, the learning of current learning path is finished.

If a learning goal is reached, the pheromone concentration will be updated in the current learning path, which called global updating strategy of pheromone and put the new personality learning path into the original learning path set.

Global updating strategy is used to update the pheromone concentration according to the test scores of *J*, after the learner finished one learning path *J*. Formula (14) shows the details of global updating strategy.

$$\tau_{ij}(\mathrm{t}+1) = \begin{cases} (1-\rho)\times\tau_{ij}(\mathrm{t}) + \Delta\tau_J^k(t), & L_i \to L_j \in J \\ (1-\rho)\times\tau_{ij}(\mathrm{t}), & L_i \to L_j \notin J \end{cases} \quad (14)$$

Where, $\Delta\tau_J^k$ is the measurement result of learning path *J*.

V. EXPERIMENT

A. The contents of experiment

A simulation experiment is used to validate the proposed recommendation algorithm, and confirm whether the algorithm can improve the efficiency of learning. The details of simulation experiment are described as follows.

The micro-learning units belong to four areas which are UI Development, Back-end Development, Mobile Development and Data Processing respectively. In details, each micro-learning goal contains a number of courses or standard learning path; each course consists of several micro-learning units. The courses providers give the standard learning paths according to domain knowledge.

Each micro-learning unit only belongs to one standard learning path. And the length of study time of each micro-learning unit is not more than 15 minutes. The standard learning paths are shown as Table 1.

TABLE 1
THE INFORMATION OF MICRO-LEARNING UNITS

Knowledge area	**Number of standard path**	**Number of knowledge level**		
		1	***2***	***3***
UI Development	45	9	20	16
Back-end Development	45	10	20	15
Mobile Development	39	9	17	13
Data Processing	37	11	11	15

There are 80 learners are invited to join this experiment, in which, they are divided into two groups named Group A and Group B equally. Pretests are used to confirm there is no large difference between two groups of learners. The details of knowledge areas and learners are described in Table 2.

TABLE 2
THE DISTRIBUTION OF LEARNERS

Knowledge area		**Number of learners**	**Number of knowledge levels**		
			1	***2***	***3***
UI Development	Group A	10	3	5	2
	Group B	11	2	5	4
Back-end Development	Group A	11	4	4	3
	Group B	11	2	5	4
Mobile Development	Group A	10	2	5	3
	Group B	9	2	4	3
Data Processing	Group A	9	2	4	3
	Group B	9	3	3	3
Sum	Group A	40	11	17	12
	Group B	40	9	17	14

The learners of Group A are required to use the standard learning path, and the learners of group B are required to use the recommended learning path based on the proposed algorithm. The learning effects can be shown by comparing test scores of two groups.

B. The analysis of experiment results

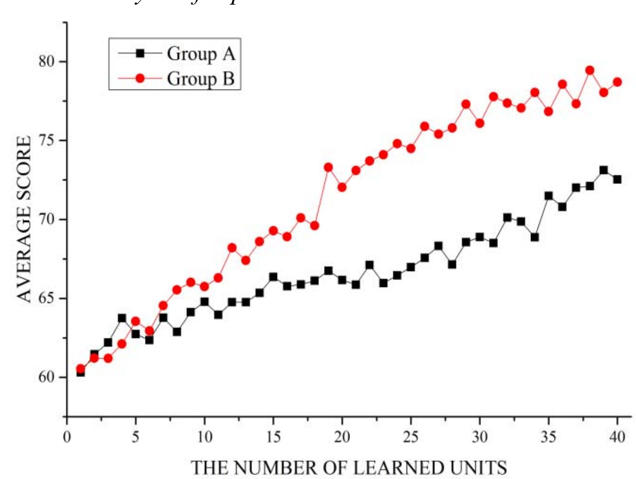

Figure 2 the experimental results of test scores

The experimental results show that the improved algorithm can improve the learning efficiency. As shown in Fig 2, the average test scores of Group B is higher than Group A generally. Even if the scores of Group A is higher than Group B in the beginning period, the average scores of Group B is higher than Group A about 5 points at the end of learning.

In the beginning period, the accumulation of pheromone concentration is low; therefore, the accuracy of recommending learning units is low. And then, the accuracy of recommendation becomes higher gradually. In the end, the proposed algorithm may be fall into local optimum because the increments of average scores become slow.

VI. CONCLUSION

This paper proposed an improved ant colony algorithm to optimize the micro-learning path. The improved algorithm is used to recommend the micro-learning units to target learners according to their transitions, and generated a dynamic learning path during the learning process. The results indicate that the improved algorithm can improve the learning efficiency.

In the late of algorithm running, the improved algorithm tends to fall into local optimum. This problem will be solved by adjusting the parameters of algorithm in the future, such as the coefficient of pheromone evaporation. Furthermore, the other algorithms such as genetic algorithm are also considered to optimize the parameters.

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