Indian J.Sci.Res. 5(1) : 17-24, 2014

ISSN : 0976-2876 (Print)
ISSN : 2250-0138 (Online)

A NEW PERSONALIZED LEARNING PATH GENERATION METHOD: ACO-MAP

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ABSTRACT

Personalized curriculum sequencing is an important issue to achieve learning goal especially in e-learning systems. The main challenge of the traditional teaching system is providing courses suitable to different learners with different knowledge background. Therefore, many researchers developed adaptive learning path systems in order to promote the effectiveness and performance of learning process. Furthermore, an optimal adaptive learning path can help the learners in reducing the cognitive overload and disorientation. In this paper, a novel two stages adaptive learning path algorithm, which is called ACO-Map is proposed. Discovering groups of learners according to their knowledge patterns is performed based on the results of pre-test, in first stage. Then in second stage ant colony optimization as a metaheuristic method is applied to find a learning path based on Ausubel Meaningful Learning Theory. The investigation emphasizes the association between the learning content and the knowledge level of each learner in adaptive learning. The output of this algorithm is an adaptive learning path for each group of learners according to their needs.

KEYWORDS : Adaptive learning path, Ant colony optimization, Concept map, E-Learning

Learning path is a sequence of concepts and activities that learner choose or must be chosen during the learning process. In the traditional learning systems the learning paths and content were defined by a few designers or experts. Therefore all the learners studied same learning content in the same order. On the other hand, each individual learner has different goal and characteristics (e.g. knowledge background, learning style, etc) from each other. in the traditional approach, a fixed sequence of learning materials is taught to the different learners. Consequently, most of the learners cannot find the most suitable learning object or concepts in a freely browsing learning environment.

But nowadays with the fast development of information and communication technologies, various teaching and learning approaches such as e-learning environments and intelligent tutoring systems come to the scene. As a result, personalization and developing an adaptive educational system become an inseparable part of learning process. The orientation of recent researches in this field classified in two main groups. The first group emphasizes on the adaptive aspect of learning systems. While the second group emphasizes the efficiency of such systems. Among these research fields, constructing adaptive learning paths to suit learners' needs is an important issue in today's adaptive educational system. Because the learners' knowledge, backgrounds, and preferences are different and choosing the same learning path for all of them has lead to a decrease in performances and satisfactions.

To achieve efficiency, the e-learning systems are modeled as a directed graph where each node represents a learning object or learning unit. Each learning object may contain one or more concept, object, image, or an audio session. In this graph, two nodes are connected if there exist a dependency relation, such that one node is a prerequisite to the other.

In this paper we proposed a method based on the meaningful learning theory and concept map to provide efficiency and personalizing the learning path using ant colony optimization algorithm to achieve adaptivity.

According to the Ausubel theory, learning process occurs meaningfully when new concepts are linked to existent ones in conceptual structure of learner. Therefore by using this property of concept map, adaptive learning path that has nearest familiar to the learner is constructed.

Ant colony optimization algorithm is a soft computing method that can handle uncertainty and incompleteness of a problem and construct the path that has maximum adaptation. This study proposes an algorithm based on the ant colony optimization technique and the idea of concept map to automatically construct the suitable learning path that can adapt to the learners.

This paper is organized as follows: in section II

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some related works about an adaptive learning path and the role of concept map as a tool to provide adaptation in learning path are discussed; in section III the proposed method is described which includes test preprocessing, K-means clustering, and ant colony optimization algorithm; To describe the operation of ACO-Map algorithm, the results is proposed in section IV; in section V the main features of proposed method are presented and a comparison of all important and basic aspects of adaptive learning path methods is done; finally conclusion and future work are presented in section VI.

I. Related works

In this section, we will define the adaptive learning path and discuss constructing concept map as a useful guidance tool for achieving this adaptation in the learning path.

A learning path is a sequence of activities and concepts with designated goals to help learners build up their knowledge or skills in a subject area. Adaptive learning path is constructed of learners' properties model that provides specific content and services according to their knowledge, backgrounds, and preferences to meet individual or group learning needs. Presenting an optimal and adaptive learning path in a learning system can improve effectiveness and performance of the learning process. To achieve this purpose in e-learning environment, a large number of methods have been proposed by researchers.

(Chen, 2011) proposed personalized diagnosis and remedial learning system (PDRLS) that providing remedial learning paths for individual learners based on their knowledge structure. In this system, first the concepts and relationship among them must be defined by experts. Then based on the results of learners' pre-test and by using Pathfinder network algorithm, learner knowledge structure can be elicited. Finally by comparing two knowledge structures, misconceptions and remedial learning path are constructed. Some of these researches also considered learning style in constructing learning path. (Sengupta et al., 2012) found relations between the terms by applying frequent graph pattern which can be created from repository of learning object. Then the ant colony optimization is applied to construct learning path between terms. Besides, for achieving to adaptivity in sequence of concepts, Evolutionary algorithms such as genetic algorithm are used. (Chen, 2008) presented a genetic-based curriculum sequence method for construct personalized learning path. The fitness function of genetic algorithm in this method is based on concepts difficulty and concepts relation degree. The concept difficulty obtained from Item Response Theory and concept relation degree calculated by using tf-idf algorithm and cosine-measure similarity.

Concept map is a tool for organizing and representing knowledge that includes concepts in the forms of circles or boxes and connecting line between them as relationships. Concept map proposed by Joseph D. Novak for first time at Cornell University in the 1960s (Novak and Cañas, 2008). The idea of his work was based on the Meaningful Learning Theory of Ausubel. Ausubel said that learning process occurs when new concepts are linked to existent ones in conceptual structure of learner.

In the effective and meaningful learning process, the learning of the concepts should be done in a proper sequence. Since the constructed concept maps based on the learners' knowledge can make the relationships between concepts more organized and adapted and present the proper learning order of concepts, therefore a large number of studies have focused on automatically constructed concept map as a useful guidance tool for adapting learning path.

(Lee et al., 2009) presented a method based on Apriori algorithm for concept map to automatically construct concept maps which can develop an intelligent concept diagnostic system (ICDS). Then by using constructed concept map, Lee et al. determine the learning barriers and suggest Remedial-Instruction Path (RIP). (Hung and Hung; 2009) presented a method to construct concept map based on Look Ahead Fuzzy Association Rule Mining Algorithm. In this method, firstly the familiar degree of concepts of learners are calculated, fuzzification of familiar degrees are done, and fuzzy association rules based on four association rule types are mined. Finally, concept map as an adaptive learning path is constructed by using mined association rules between concepts.

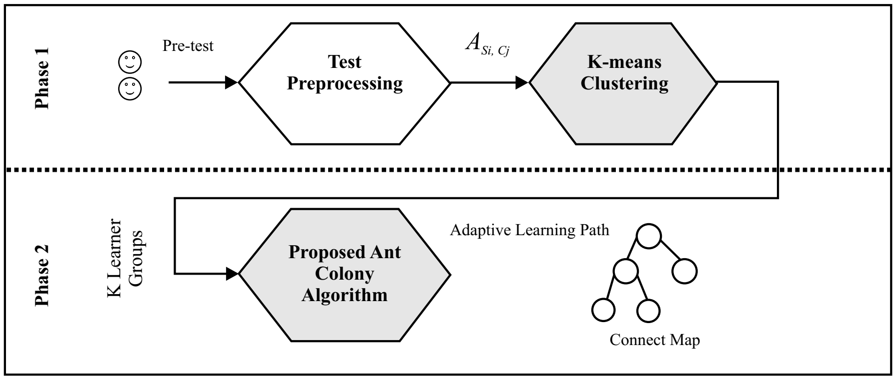

Figure 1: Two stage approach to construct adaptive learning path

II. The proposed of adaptive learning path

`As shown in Figure 1, this study presents a novel two-stage approach to construct adaptive learning path which is called ACO-Map. In the first stage of this method, K-means algorithm is used to divide learners into groups of learners which have a similar familiarity to the concepts. Then ant colony optimization is applied to construct a learning path for each group as their guidance tool for adaptive learning path in second stage. The process of proposed method will be explained in the following sections.

A. Test Preprocessing

Assuming that each learning object has C concepts and there are N concepts in each test item ($1 \le N \le C$). The relevance degree between concept *Cj* and test item *Qi* is shown by $R_{Qi,Cj}$. The greater value of $R_{Qi,Cj}$, denotes the more relevance between test item *Qi* and concept *Cj*, $R_{Qi,Cj}$. When the test item *Qi* only contains the concept *Cj* $R_{Qi,Cj}$, will be represented by "1". When the test item *Qi* does not contain concept *Cj* $R_{Qi,Cj}$, will be represented by 0 ($0 \le R_{Qi,Cj} \le 1$).

Assuming that S learners take *Q* test items. $P_{si,Qj}$, indicates the score of the learner *Si* in test item *Qj*. Scores are graded in *P* scale ($0 \le P_{si,Qj} \le P$).

In order to estimate the learners' familiar degree of concepts, $P_{si,Qj}$ and $R_{Qi,Cj}$ should be considered together. $A_{Si,Cj}$ indicates the familiar degree of the learner *Si* about the concept *Cj* , where

$$A_{S_i, C_j} = \left(\frac{1}{P} \sum_{k=1}^{Q} P_{S_i, Q_k} R_{Q_k, C_j} \right) \Bigg/ \sum_{k=1}^{Q} R_{Q_k, C_j} \qquad (1)$$

where $0 \le A_{Si,Cj} \le 1$ (Hung and Hung; 2009).

B. K-means Algorithm to Learner Clustering

Learners can be cluster according to their familiarities degrees of the concepts. $A_{Si,Cj}$ is familiar degree [SxC] matrix, which S is a number of learners and C is a number of concepts in a learning object.

K-means clustering is an iterative clustering method, and divides the data into a predefined number of clusters. The K-means algorithm is a non-hierarchical approach to forming good clusters based on measuring similarities of instances. After clustering step, each learner in a cluster will have nearly similar familiarities in each concept. Therefore, the learning background of each group can be used in next step to construct adaptive learning path for their members.

C. Ant Colony Optimization

Ant colony is a part of swarm intelligence approach that has been successfully used in the general purpose optimization techniques. Ant colony optimization (ACO) is a randomized search method based on the foraging behavior of some ant species. These ants deposit same amount of pheromone on their paths in order to mark some favorable path that should be followed by other members of the colony, so shorter paths will receive more pheromone per time unit. Furthermore, the amount of pheromone on each path decreases as time passes because of evaporation. Therefore, longer paths lose their pheromone intensity and become less favorable over time (Dorigo; 1992).

ACO algorithms can be used in any optimization problem, if the following aspects are provided:

Graph Construction

In this problem, nodes represent concepts and the edges between them denote the choice of studying the next concept respectively in learning path. Nodes are fully connected. The search for the optimal learning path is finding the best arrangement of nodes (concepts) that helps a group of learners to understand the learning topic better.

Solution construction

Each ant starts randomly to choose starting concept and in each iteration adds an unvisited concept to its partial tour. At each step, each ant constructs a solution. Then each ant will share its solution feedback by updating a pheromone matrix with the entire colony. Each entry in the pheromone matrix shows the desirability of each concept. At the end of each iteration, the pheromone associated with each solution component is reinforced based on the quality of the solution that comprises the particular solution component. In subsequent iterations, ants will use the pheromone intensities of available solution components to guide whole solution construction. As a result of repeated pheromone reinforcements, a subset of solution components will emerge to have pheromone intensities much higher than the others. The solution construction terminates when it can satisfy the stopping criterion (e.g. group of learner hasn't any misconception in learning subject).

Pheromone trails and heuristic information

Let S be a set of given N concepts in a learning object, and be the pheromone level (desirability measure) of concept c to be in the selected subset of concepts s where . Initially, the desirability of each concept will be the same, but the desirability of those concepts which are more important, increases in each step. A concept map which is constructed by instructor is suggested to be used for heuristic information. This concept map is based on the Meaningful Learning Theory of Ausubel, so more general concepts which are placed on the top of the graph should have more rank and more specific ones which are placed at the bottom of the graph should have less rank in heuristic information (is a heuristic information for concept i).

The ants build solutions applying a probabilistic decision policy to choose next node. In this case each subset of concept represents a state. The state transition rules help ants to select concepts using the pheromone trail and the heuristic value. Each ant chooses a particular concept by maximizing a product of these two parameters (Sivagaminathan and Ramakrishnan; 2007). An ant m chooses a concept i in its solution at time step t as follows:

$$P_i^m(t) = \begin{cases} \dfrac{[\tau_i(t)]^{\alpha} \cdot [\eta_i]^{\beta}}{\sum_{u \in J^m} [\tau_u(t)]^{\alpha} \cdot [\eta_u]^{\beta}} & if \quad i \in C^m \\ 0 & otherwise \end{cases} \tag{2}$$

Where C^m is the set of feasible concepts that can be added to the partial solution for ant m; $\alpha \geq 0$ and $\beta \geq 0$ are two parameters that determine the importance of the pheromone value and heuristic desirability.

Pheromone update rule: After an ant has completed its tour, the amount of pheromone deposited on the edges of this tour is used in updating rule. First, this amount of pheromone trail (τ) should be decreased by an evaporation factor (ρ);

$$\tau_i(t) \quad (1-\rho)*\tau_i(t) \tag{3}$$

Second, each ant retraces the path which it has followed and deposits an amount of pheromone on each traversed connection; the pheromone updating rule is defined as:

$$\tau_i(t) \leftarrow \tau_i(t) + \sum_{k=1}^{m} \Delta\tau_i^k(t) \tag{4}$$

Where the pheromone is updated according to the measure of the desirability of the ant's concept subset. $\Delta\tau_i(t)$ is the familiar degrees $A_{sm,Cj}$(eq. 1) of traversed concepts *Cj* by ant m (learner) at iteration *t*. The pseudo code of proposed algorithm (ACO-Map) is presented in figure 2.

RESULTS

To obtain a fast and efficient result, ACO-map algorithm implemented in Matlab environment. To describe the operation of algorithm step by step, let us consider 20 concepts in the course, 6 test items, and 1000 ants (learners) to construct the adaptive path. In the training phase of algorithm, ant colony optimization method needs a large number of ants to achieve convergence. Thus the scores of 1000 learners are generated randomly to assign them to ants. Then in the test phase, a real learner enters to system, takes pre-test, assigns to near cluster, and finally a learning path is shown to her/him according to nearest cluster. The

Input: A_{S_i,C_j}

Input for ACO: number of ants and ACO's parameters (α,β,p and k cluster)

Output: Adaptive learning path (a concept map for each group of learners)

1: Do k-means clustering on A_{S_i,C_j}

2: Do (for each cluster) {

3: Set the same value for pheromone and heuristic information

4: % Ant generation

5: Assign a concept to each ant randomly

6: Do (for each Ant)

{

7: Calculate State Rule (Eq. 2)

8: Choose next concept (according the step 7)

9: If there isn't any concept (C_j) with familiarity less than 0.7 in A_{S_m,C_j}

10: Continue;

11: }

12: Check the termination condition (if iteration number finished or if there isn't any learner in groups with familiarity to a concept less 0.7 in post test)

13: Return best path

14: Update the pheromone of all ants (Eq. 3 and 4)

15: Go to step 6 and continue. }

Figure 2 : Proposed adaptive path learning algorithm base on ACO

relevance degree between these concepts and test items is shown in table 1.

Besides, the score of learners in test items in cluster 1 shown in table 2 (scores are graded in 20). Then familiar degree is calculated by using table 1 and table 2. The familiar degree of learners in cluster 1 is shown in table 3. For ant 3 and concept 4, $A_{Si,Cj}$ is calculated as follow:

AS3, C4 = [1/20*(3*0 + 17*0.2 + 12*0.2 + 20*0 + 17*0 + 4*0 + 2*0 + 0*0.2 + 12*0 + 15*0 + 18*0 + 3*0)] / (0.2 + 0.2 + 0.2) = 0.483

In the ant colony optimization phase, nodes are fully connected in graph construction. At the first, the desirability of each concept is same, but the desirability of each concept that is more important, increases in each step. For the heuristic information, a concept map constructed by expert is suggested. Therefore each node of graph that is placed on top of the concept map should have more rank and vice versa. The heuristic information (η) of this example with 20 concepts is shown in table 4.

In the testing phase, a real learner with following calculated familiar degree with concepts (table 5) enters to the system. The familiar degree of this learner is most similar to cluster 1, thus the learner should be assigned to cluster 1.

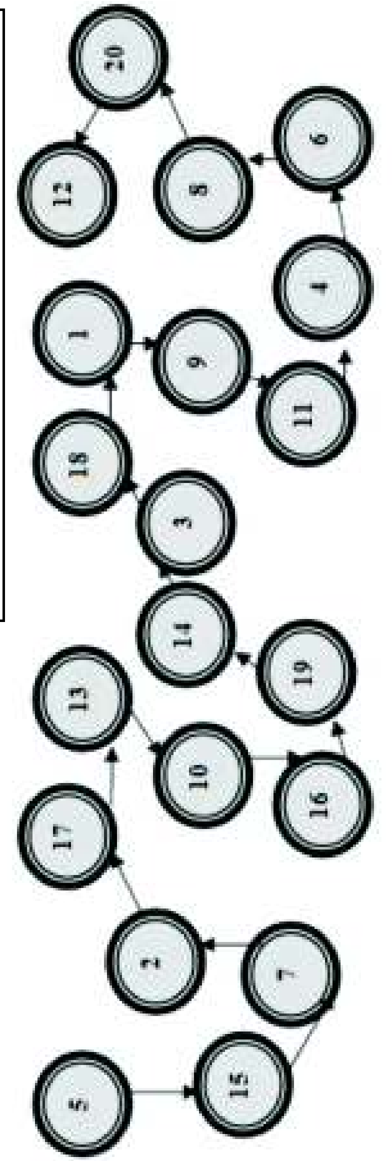

Figure 3 : The adaptive learning path

Finally the adaptive learning path for cluster 1 is shown in Figure 3. The numbers on the circles show the number of concept and arrows indicates the order that should learners follow to learn concepts. For example this learner has most familiar degree with concept 5 and therefore this concept should be learned first.

DISCUSSION

In this work, we proposed a novel method to build an adaptive learning path by using the combined features of clustering and ant colony algorithms. On the other hand, it is based on a well-known learning theory. Therefore, its output

Table 1 : Relevance degree

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20
Q1	0.1	0	0.1	0	0	0	0.1	0	0.1	0	0	0	0.1	0.1	0	0.1	0.1	0.1	0	0
Q2	0	0	0	0.2	0	0	0	0	0.2	0	0	0	0.2	0.1	0.2	0	0	0	0.1	0
Q3	0	0.1	0	0.2	0.1	0	0	0	0.1	0.1	0.1	0	0	0.1	0	0.1	0	0.1	0.2	0
Q4	0	0	0	0	0.3	0	0	0	0	0	0	0.1	0	0	0.1	0.2	0.2	0	0	0.1
Q5	0.2	0	0	0	0	0.2	0	0	0	0.1	0.1	0	0	0	0.2	0	0	0.2	0	0
Q6	0	0	0	0	0	0	0	0	0.4	0	0	0	0.1	0	0.1	0	0	0	0	0.4

Table 2 : Learners score

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12
L3	3	17	12	20	17	4	2	0	12	15	18	3
L6	4	14	16	19	13	3	3	17	4	18	5	12
L14	8	15	17	9	9	3	15	1	9	11	11	19
L16	19	14	10	19	13	17	13	18	15	20	16	1
…	…											

Table 3 : Familiar degree

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20
L3	0.708	0.600	0.375	0.483	0.675	0.333	0.400	0.285	0.479	0.441	0.725	0.550	0.438	0.533	0.600	0.687	0.470	0.458	0.700	0.510
L6	0.366	0.800	0.333	0.783	0.781	0.700	0.350	0.478	0.433	0.591	0.725	0.550	0.544	0.566	0.495	0.725	0.480	0.583	0.800	0.395
L14	0.475	0.850	0.608	0.550	0.537	0.483	0.633	0.392	0.479	0.383	0.650	0.600	0.644	0.666	0.513	0.537	0.560	0.675	0.750	0.350
L16	0.766	0.500	0.550	0.700	0.762	0.533	0.600	0.800	0.808	0.741	0.575	0.800	0.661	0.716	0.754	0.837	0.830	0.475	0.675	0.860
…	…																			

Table 4 : The heuristic information

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20
	7	10	3	1	11	9	20	17	15	19	12	18	16	13	14	8	4	5	2	6

Table 5 : Familiar degree of the learner

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20
learner	0.500	0.477	0.487	0.500	0.812	0.525	0.450	0.468	0.550	0.775	0.630	0.436	0.487	0.678	0.622	0.625	0.620	0.493	0.500	0.330

Table 6 : Comparisons table for different methods

	Method	Based on Learning Theory	Pretest	Optimization	Adaptivity	Extract Relations Between Concepts/Learning Object
(Lee et al., 2009)	Apriori Algorithm (for constructing concept map)	(Ausubel meaningful learning theory)	for knowledge level	×		Semi automatic
(Hsu and Ho, 2012)	fuzzy interpolation, ant-genetic algorithm	×				Semi automatic
(Anh et al., 2008)	Bayesian Belief Network	×		×		Semi automatic
(Chen, 2011)	Pathfinder network algorithm			×		Semi automatic
(Chen, 2008)	Genetic algorithm	×				Automatic
(Sengupta et al., 2012)	Ant Colony Optimization	×	×		×	Semi automatic
ACO-Map	Concept Map + Ant Colony Optimization	(Ausubel meaningful learning theory)	for knowledge level			Automatic

is a concept map for each group of learners.

In recent years, several methods have been proposed to adapt a learning path based on learners' knowledge, backgrounds, and preferences. In table 6, the basic features of adaptive learning path methods are presented and compared in detail.

CONCLUSION

In this paper, we proposed a novel two-stage approach to construct adaptive learning path which is a concept map. Since obtained sequencing of concepts are based on the familiar with learners' knowledge, therefore according to Ausubel theory, by using constructed adaptive path, new concepts will be linked to existent ones and effectiveness and performance of the learning process can be improved.

Contributions of this paper are: a) considering the idea of meaningful learning theory in constructing learning path; b) clustering learners based on learners' familiar degree of each concept; c) applying ant colony optimization algorithm in combination with concept map to achieve adaptive learning path for each groups of learners.

As a further enhancement to this study: a) this algorithm should be tested and evaluated on the real learners and courses; b) the test item-concept relevance table can be constructed automatically; c) for clustering learners in the first stage, fuzzy c-means algorithm for better adaptation can be used, because each of learner can map to more than one cluster and therefore more than one optimal adaptive learning path can obtain for each learner.

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