Ontology-based Concept Map for Planning Personalized Learning Path

Chih-Ming Chen
Graduate Institute of Library, Information and Archival Studies, National Chengchi University, Taipei 116, Taiwan, R.O.C.
chencm@nccu.edu.tw

Chi-Jui Peng
Graduate Institute of Learning Technology, National Hualien University of Education, Hualien 970, Taiwan, R.O.C.
chi_jui_1109@yahoo.com.tw

Jer-Yeu Shiue
Graduate Institute of Learning Technology, National Hualien University of Education, Hualien 970, Taiwan, R.O.C.
jeryeu@gmail.com

Abstract—**Developing personalized Web-based learning systems has been an important research issue in the e-learning field because no fixed learning pathway will be appropriate for all learners. However, the current most web-based learning platforms with personalized curriculum sequencing tend to emphasize the learners' preferences and interests for the personalized learning services, but they fail to consider difficulty levels of course materials, learning order of prior and posterior knowledge, and learners' abilities while constructing a personalized learning path. As a result, these ignored factors easily lead to generating poor quality learning paths. Generally, learners could generate cognitive overload or fall into cognitive disorientation due to inappropriate curriculum sequencing during learning processes, thus reducing learning effect. With advancement of the artificial intelligence technologies, ontology technologies enable a linguistic infrastructure to represent concept relationships between courseware. Ontology can be served as a structured knowledge representation scheme, which can assist the construction of personalized learning path. Therefore, this study proposes a novel genetic-based curriculum sequencing scheme based on a generated ontology-based concept map, which can be automatically constructed by a large amount of learners' pre-test results, to plan appropriate learning paths for individual learners. The experimental results indicated that the proposed approach is indeed capable of creating learning paths with high quality for individual learners. This will be helpful to learners to learn more effectively and to likely reduce learners' cognitive overloads during learning processes.**

Keywords—**ontology-based concept map, personalized learning path, web-based learning**

I. INTRODUCTION

A few researchers brought up an idea to use the learning path as a control way to guide the learning direction for individual learners. More and more researches attempt to create intelligent learning systems that can arrange the curriculum sequence more flexibly in order to provide learners with more adaptive and personalized learning services [1-6]. However, these intelligent learning systems are not so adaptive to individual learners because learners' abilities, difficulty levels of course materials and learning sequences of prior and posterior knowledge between courseware have not been considered yet in these systems. Although the genetic-based personalized learning path generation scheme, which can provide a near optimal learning path for individual learners on-line according to the difficulty levels of course materials, concept relation degree between courseware and learners' abilities, was presented by our previous study [7], the learning order of prior and posterior knowledge is ignored. This leads to illogical learning paths while planning a personalized learning path for individual learners.

Ontology [8-11] is a hierarchically structured set of terms for describing a domain knowledge that can be used as a skeletal foundation for a knowledge base system. If an ontology is implemented for a specific field well and used to describe the related knowledge such as terminology or associated notions, it can help us find out useful or connected information when we explore under this kind of structured knowledge. Therefore, this research aims to improve the shortcoming of the genetic-based personalized learning path generation scheme presented in our previous study [7], such that the learning order of prior and posterior knowledge can be considered while planning personalized paths. This study expects to establish authentic and near optimal learning paths that can help individual learners reduce the effects of cognitive overload and disorientation. Experimental results show that the proposed genetic-based learning path generation scheme based on ontology-based concept map is superior to the genetic-based learning path generation scheme proposed in our previous study in terms of learning path quality because of simultaneously considering the difficulty of courseware, prior and posterior knowledge of learning concepts, and learners' abilities while planning personalized paths.

II. THE PROPOSED SCHEME

This section is organized as follows: first, Section A aims to explain the proposed ontology-based concept map generation scheme. Section B presents how to applying the generated ontology-based concept map to personalized learning path generation.

A. The Proposed Ontology-based Concept Map Generation Scheme

1) The designed course materials in the course unit "fraction" for exploring ontology-based concept map

Currently, the proposed system contains one course unit "Fraction" and includes 17 course materials designed by several mathematical teachers based on four version mathematical textbooks (i.e. Han Lin, Nani, Jenlin, and Kang

978-1-4244-1674-5/08 /$25.00 ©2008 IEEE

Hsuan) used in Taiwan's elementary schools. Each course material has a corresponding difficulty parameter, initially determined by statistics analysis according to a pre-test, and each courseware corresponds to several testing questions which can be employed to examine whether the learned courseware can be understood. In this study, there is a learning portfolio database storing testing records of more than 600 elementary school students who participated in the exam in the "Fraction" unit. In the exam, the learned courseware with wrong answer will be served as "focused concept" to evaluate the correlation with the other courseware with wrong answer as well for the proposed ontology-based concept map generation scheme. All designed course materials for the learning process and their corresponding difficulty parameters are listed in TABLE I.

TABLE I. THE CONTENTS OF THE DESIGNED COURSE MATERIALS AND THE DIFFICULTY LEVELS OF THE CORRESPONDING COURSE MATERIALS IN THE COURSE UNIT "FRACTION

Course material	The difficulty level of course material
C1 (Equal parts)	-1.8
C2 (Division as sharing)	-1.5
C3 (Division as separating)	-1
C4 (Sharing with a remainder)	-0.1
C5 (Separating with a remainder)	0
C6 (Parts of a whole)	0.1
C7 (Improper fractions)	0.2
C8 (Sequence of fractions)	0.4
C9 (Compare proper fractions with the same denominator)	0.5
C10 (Compare proper fractions with different denominators)	0.7
C11 (Add and subtract fractions)	1.2
C12 (Adding fractions)	0.8
C13 (Subtracting fractions)	1
C14 (Missing addend)	1.3
C15 (Missing subtrahend)	1.5
C16 (Missing summand)	1.6
C17 (Missing minuend)	1.8

2) The computing method of concept correlation for exploring ontology-based concept map

According to the result of a testing question exam, this study proposes a computing formula of correlation to calculate the concept relationships between courseware. And the adopted mathematical formula is as follows,

$$R_{C_i,C_j} = P(C_j|C_i) = \frac{N(C_i \cap C_j)}{N(C_i)} \quad (1)$$

where R_{C_i,C_j} represents the concept relation between the i^{th} learning concept and the j^{th} learning concept, $N(C_i)$ is the number of the learners who gave wrong answer for the corresponding testing question that conveys the i^{th} learning concept, and $N(C_i \cap C_j)$ stands for the number of the learners who simultaneously gave wrong answers for the corresponding testing questions that conveys both the i^{th} and j^{th} learning concepts.

In other words, the concept relationships between courseware are evaluated based on learners' responses in a testing question exam. All correlations among the 17 designed course materials in the "Fraction" unit can be evaluated and represented as a concept correlation matrix. Moreover, the threshold chosen to filter out weak concept correlations is heuristically set to 0.132 in the study. The goal is to filter out the concept connections with weak correlation to each other. This process can simplify the generated ontology-based concept map. Actually, heuristically setting the threshold in the study is a trade-off consideration based on the convergence speed and the quality of the planning personalized learning path.

3) The proposed ontology-based concept map generation scheme based on the computing concept correlations and fuzzy clustering scheme

a) Concept map generation based on fuzzy clustering scheme

In this section, how to use the fuzzy clustering analysis scheme [12] to group courseware with high correlation into the same clusters will be introduced. In the employed fuzzy clustering analysis scheme, the clustering result will be affected by different α-cuts [12]. To optimize the clustering result, the concept correlations within the same cluster are expected as high as possible, but the ones between different clusters are expected as low as possible. Thus, the cost function, which integrates maximizing the concept correlations in the same cluster and minimizing the concept correlations among different clusters, was employed to determine best appropriate number of clusters. The final clustering outcome under considering optimal number of clusters is listed in TABLE II.

The ontology-based concept map can be depicted according to the clustered courseware by the fuzzy clustering algorithm and the asymmetric concept correlation matrix. The following descriptions details how to construct a concept map:

Step 1: Constructing the inner correlations

Here, we only need to consider the clusters that contain more than one courseware, such as Cluster 1 and Cluster 8. Taking Cluster 1 as example, we can first find out all correlations between the 6 courses and draw connections where their weights can be indicated based on the asymmetric concept matrix. To simplify the generated ontology concept map, this study only considers connecting the concepts with top five high correlation values. Thus, the ontology concept map of the Cluster 1 can be shown as Fig. 1. The same method can be applied to construct the ontology concept map of the Cluster 8.

TABLE II. THE RESULT OF CONCEPT CLUSTERING BY THE FUZZY CLUSTERING SCHEME

The clustering results based on concept correlations among courseware	**The clustered set of courseware**
Cluster 1	C4 (Sharing with a remainder) 、C5 (Separating with a remainder)、C9 (Compare proper fractions with the same denominator)、C1 (Equal parts)、C17 (Missing minuend)、C12 (Adding fractions)
Cluster 2	C6 (Parts of a whole)
Cluster 3	C3 (Division as separating)
Cluster 4	C8 (Sequence of fractions)
Cluster 5	C2 (Division as sharing)
Cluster 6	C7 (Improper fractions)
Cluster 7	C10 (Compare proper fractions with different denominators)
Cluster 8	C11 (Add and subtract fractions) 、C15 (Missing subtrahend) 、C13 (Subtracting fractions)
Cluster 9	C16 (Missing summand)
Cluster 10	C14 (Missing addend)

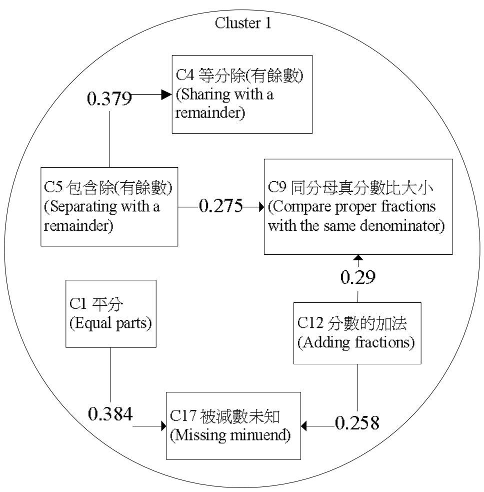

Figure 1. The generated ontology concept map of the cluster 1

Step 2: Constructing the outer correlations and calculating the weights of correlations between any two clusters

In this step, the main idea of constructing ontology concept map is similar to Step 1. Based on the clustering results of TABLE II, the totally needed number of connections to link each cluster is 9 because of 10 concept clusters in the case. Next, this study employed a similarity measure to estimate the weights of correlations between two clusters, and formulated as follows:

$$weight_{i,j} = \frac{\sum_{p=1}^{n_i}\sum_{q=1}^{n_j} rel(C_{i,p}, C_{j,q})}{n_i \times n_j}, \quad where\ 0 \le weight_{i,j} \le 1,\ 1 \le i,j \le n \qquad (2)$$

where $weight_{i,j}$ is the correlation between the i^{th} cluster and the j^{th} cluster, n_i is the number of courseware in the i^{th} cluster, n_j is the number of courseware in the j^{th} cluster, and $rel(C_{i,p}, C_{j,q})$ is the correlation between the p^{th} courseware in the i^{th} cluster and the q^{th} courseware in the j^{th} cluster.

The complete ontology-based concept map is displayed as Fig. 2.

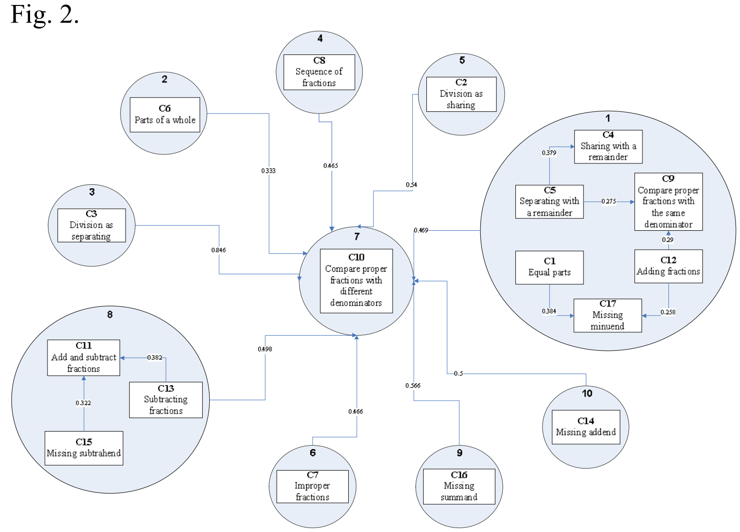

Figure 2. The generated ontology-based concept map for the 17 designed courseware

b) Courseware teaching sequence pattern derived from the ontology-based concept map

Based on the generated ontology-based concept map shown as Fig. 2, 23 courseware teaching sequence patterns are summarized and listed in TABLE III. In the teaching sequence of each courseware, premise part can be viewed as prior knowledge of conclusion part. This property is beneficial to planning a logical learning path while providing curriculum sequencing for personalized learning services.

TABLE III. THE COURSEWARE TEACHING SEQUENCE PATTERN DERIVED FROM ONTOLOGY-BASED CONCEPT MAP

No.	Courseware teaching sequence pattern	No.	Courseware teaching sequence pattern
1	C1(Equal parts) → C10 (Compare proper fractions with different denominators)	13	C11 (Add and subtract fractions) → C10 (Compare proper fractions with different denominators)
2	C1 (Equal parts) → C17 (Missing minuend)	14	C12 (Adding fractions) → C9 (Compare proper fractions with the same denominator)
3	C2 (Division as sharing) → C10 (Compare proper fractions with different denominators)	15	C12 (Adding fractions) → C10 (Compare proper fractions with different denominators)
4	C3 (Division as separating) → C10 (Compare proper fractions with different denominators)	16	C12 (Adding fractions) → C17 (Missing minuend)
5	C4 (Sharing with a remainder) → C10 (Compare proper fractions with different denominators)	17	C13 (Subtracting fractions) → C10 (Compare proper fractions with different denominators)
6	C5 (Separating with a remainder) → C4 (Sharing with a remainder)	18	C13 (Subtracting fractions) → C11 (Add and subtract fractions)
7	C5 (Separating with a remainder) → C9 (Compare proper fractions with the same denominator)	19	C14 (Missing addend) → C10 (Compare proper fractions with different denominators)
8	C5 (Separating with a remainder) → C10 (Compare proper fractions with different denominators)	20	C15 (Missing subtrahend) → C10 (Compare proper fractions with different denominators)
9	C6 (Parts of a whole) → C10 (Compare proper fractions with different denominators)	21	C15 (Missing subtrahend) → C11 (Add and subtract fractions)
10	C7 (Improper fractions) → C10 (Compare proper fractions with different denominators)	22	C16 (Missing summand) → C10 (Compare proper fractions with different denominators)
11	C8 (Sequence of fractions) → C10 (Compare proper fractions with different denominators)	23	C17 (Missing minuend) → C10 (Compare proper fractions with different denominators)
12	C9 (Compare proper fractions with the same denominator) → C10 (Compare proper fractions with different denominators)		

C. Applying Ontology-based Concept Map to Personalized Learning Path Generation

To plan more appropriate learning path than our previous study [7], the curriculum structure contained in the generated ontology-based concept map is used as the constraint conditions of the employed genetic algorithm to plan personalized learning paths for individual learners. In other words, a planning learning path by the genetic algorithm must be evaluated whether it satisfies the curriculum sequence implied in the generated ontology-based concept map. If a planning learning path by the genetic algorithm conflicts with the order of prior and posterior knowledge between courseware, it will be treated as an inappropriate learning path. To measure the quality of planning learning paths, this study proposes a penalty term α to calculate the violated value by comparing the rules of prior and posterior knowledge derived from ontology-based concept map with the generated learning path, so that those learning paths which conflict with the order of prior and posterior knowledge decline the corresponding fitness function value. Thus, a high quality learning path should get a penalty value as less as possible. The proposed penalty term is defined as,

$$\alpha = \sum_{k=1}^{n} MAX(P_{k1} - P_{k2}, 0) \tag{3}$$

where α is the proposed penalty term, n is the total number of prior and posterior knowledge rules, P_{k1} and P_{k2} are the corresponding position index values in a planning learning path which violates with the antecedent and consequent parts of the k^{th} rule of prior and posterior knowledge derived from ontology-based concept map, respectively.

To define a fitness function, which can simultaneously consider the proposed penalty term and the difficulty parameter of courseware for evaluating the quality of a generated learning path, both the considered parameters are normalized between 0 to 1 and combined by an adjustable weight. In other words, the planning learning path will satisfy that the difficult levels of courseware are from easy to hard and the curriculum sequence follows the order of prior and posterior knowledge as possible. Moreover, the courseware with the smallest difficulty parameter is always selected as the first courseware ranked in a generated learning path. The proposed fitness function for planning high quality personalized learning path is formulated as follows:

$$f = (1-w) \times (1-\alpha_n) + w \times \sum_{i=2}^{m} (b_{i(n)} - b_{i-1(n)}) \tag{4}$$

where f is the proposed fitness function for evaluating the quality of a generated learning path, α_n is a normalized penalty term for evaluating the violated value of a generated learning path with the rules of prior and posterior knowledge derived from ontology-based concept map, $b_{i(n)}$ stands for the normalized difficulty level of the i^{th} courseware, m stands for the total number of courseware considered for personalized learning path generation, and w is an adjustable weight.

III. EXPERIMENTS

The experimental analysis mainly focuses on the performance comparison of the proposed genetic-based learning path generation scheme supported by ontology concept map with the genetic-based learning path generation scheme presented in our previous study [7].

A. Parameter Setting of Fitness Function

In the study, the parameter setting for the proposed fitness function will affect the quality of the generated learning paths. In our experiments, the termination condition for the genetic algorithm is set to 150 generations, the population size is set to 50, the mutation rate is set to 0.1, and the duplication rate is set to 1. Based on our experiments, the adjustable weight for planning personalized learning paths is set to 0.7 in the study because this weight can obtain the learning path with best quality and fastest convergence speed of the employed genetic algorithm among several different weight combinations.

B. Quality Evaluation of the Personalized Learning Path Generated by the Proposed Scheme

In an educational adaptive learning system, a learning path with high quality aims to maximize a combination of the learner's understanding of courseware and the efficiency of learning the courseware. However, finding a learning path with high quality for individual learner is difficult because no standard solution exists by which to evaluate the success of a learning path with high quality. Therefore, applying the teaching sequences of textbooks and the teaching sequences suggested by experienced teachers as baseline to evaluate the quality of a learning path is a reasonable approach because the teaching sequences are main consideration to textbooks' unit formation or teachers' teaching processes. To evaluate the quality of the generated learning path, the totally violated distance of teaching sequence is defined and formulated as follows:

$$\gamma = \sum_{i=1}^{n-1} \sum_{j=(i+1)}^{n} MAX(P_i - P_j, 0) \tag{5}$$

where γ is the total value of violated distance for a planned learning path, n is the total number of course materials in a course unit, P_i is the corresponding position index value in a planning learning path which violates with the antecedent part of the i^{th} rule of prior and posterior knowledge derived from ontology-based concept map, P_j is the corresponding position index value in a planning learning path which violates with the consequent part of the j^{th} rule of prior and posterior knowledge derived from ontology-based concept map.

1) Comparing the generated learning path with the teaching sequences of four version textbook

This study assumes that a leaner performs a pre-test of the "Fraction" unit with 17 various course materials, and the learner totally occurs 17 incorrect testing items, which correspond to 17 learning concepts of the "Fraction" unit. This case represents that the proposed system will plan a personalized learning path containing the 17 course materials to guide the learning process for the learner. To evaluate the average performance of the proposed scheme for planning personalized learning path, 20 independent runs were conducted to plan personalized learning paths and each planned learning path was respectively compared with the individual teaching sequences of four version textbooks. TABLE IV summarizes the individual teaching orders and integrated teaching order of 17 designed courseware in the course unit "Fraction" obtained from the four selected textbooks.

2) Comparing the generated learning path with the teaching sequences from course expert's suggestion

In order to further evaluate the quality of the learning path generated by the proposed novel scheme, this study invited three experienced mathematical teachers who came from Kuan-Hua elementary school in Hualien of Taiwan to ask for their suggestions on the learning sequence of the 17 course materials related to the course unit "Fraction". TABLE V reveals the teaching sequence of the 17 course materials in the course unit "Fraction" suggested by 3 experienced mathematical teachers of Kuan-Hua elementary school and the integrated teaching sequence suggested by these three mathematical teachers. Similarly, 20 independent runs were conducted and respectively compared with the individual teaching sequences suggested by 3 experienced mathematical teachers of Kuan-Hua elementary school for the 17 course materials in the "Fraction" unit.

The experimental results mentioned-above are summarized in TABLE VI. Based on the results, this study demonstrates that the learning paths planned by the proposed genetic-based personalized learning path generation scheme supported by the ontology-based concept map are more accurate and reliable than those constructed learning paths by our previous proposed scheme.

TABLE IV. SUMMARIZATION OF THE INDIVIDUAL TEACHING SEQUENCES AND INTEGRATED TEACHING SEQUENCE OF THE 17 DESIGNED COURSEWARE OBTAINED FROM FOUR SELECTED TEXTBOOKS

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Han Lin	1	3	2	5	4	6	16	8	7	17	15	9	10	11	13	12	14
Nani	1	2	4	3	5	6	11	7	9	17	16	8	10	12	14	13	15
Jenlin	1	3	2	4	5	6	12	7	8	13	11	9	10	14	16	15	17
Kang Hsuan	1	2	4	3	5	6	15	7	16	17	10	8	9	11	12	13	14
Total ranking value	4	10	12	15	19	24	54	29	40	64	52	34	39	48	55	53	60
Average teaching order	1	2.5	3	3.75	4.75	6	13.5	7.25	10	16	13	8.5	9.75	12	13.75	13.25	15
The integrated teaching order	C1→C2→C3→C4→C5→C6→C8→C12→C13→C9→C14→C11→C16→C7→C15→C17→C10																

TABLE V. SUMMARIZATION OF THE INDIVIDUAL TEACHING SEQUENCES AND INTEGRATED TEACHING SEQUENCE OF THE 17 DESIGNED COURSEWARE SUGGESTED BY 3 EXPERIENCED MATHEMATICAL TEACHERS OF KUAN-HUA ELEMENTARY SCHOOL

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
Course Expert A	1	2	3	4	5	6	9	10	7	8	13	11	12	14	16	15	17
Course Expert B	1	2	3	6	7	4	8	9	5	10	14	11	12	13	17	15	16
Course Expert C	1	2	3	4	5	6	9	8	7	17	16	10	13	11	14	12	15
Total ranking value	3	6	9	14	17	16	26	27	19	35	43	32	37	38	47	42	48
Average teaching order	1	2	3	4.6	5.6	5.3	8.6	9	6.3	11.6	14.3	10.6	12.3	12.6	15.6	14	16
The integrated teaching order	C1→C2→C3→C4→C6→C5→C9→C7→C8→C12→C10→C13→C14→C16→C11→C15→C17																

TABLE VI. THE ENTIRE QUALITY EVALUATION OF THE LEARNING PATH GENERATED BY BOTH THE PERSONALIZED LEARNING PATH GENERATION SCHEMES IN 20 INDEPENDENT RUNS

Learning mode / **Comparison items**	**Genetic-based personalized learning path generation scheme [7]**	**Genetic-based personalized learning path generation scheme supported by ontology-based concept map**
The average violated distance of the generated learning path with the individual teaching sequences of the four version textbooks	470	217
The average violated distance of the generated learning path with the integrated teaching sequence of the four version textbooks	452	196
The average violated distance of the generated learning path with the individual teaching sequences of the three course experts	441	256
The average violated distance of the generated learning path with the integrated teaching sequence of the three course experts	448	292

IV. CONCLUSIONS

This study presents a novel genetic-based personalized learning path generation scheme based on ontology-based concept map, which can simultaneously consider courseware difficulty level and the concept relations of prior and posterior knowledge between courseware to plan personalized learning paths according to the incorrect testing responses in a pre-test. Experimental results indicate that the proposed scheme is capable of creating higher quality learning paths than the previous proposed genetic-based personalized learning path generation scheme for individual learners. From the point of view that the proposed system can guide individual learners to conduct adaptive learning, the proposed scheme provides benefit in terms of reducing learner cognitive overload or disorientation during learning processes. In addition, the personalized learning path customizes learning for those who have very specific needs and not much time or patience to complete topics they have learned, thus helping learners learn more effectively.

REFERENCES

[1] P. Brusilovsky, "Adaptive educational systems on the world-wide-web: a review of available technologies," In Proceeding of Workshop WWW-Based Tutoring at 4th International Conference in Intelligent Tutoring Systems, 1998.

[2] Myung-Geun Lee, "Profiling students' adaptation styles in web-based learning," *Computers & Education*, vol. 36, pp. 121-132, 2001.

[3] Tiffany Ya Tang and Gordon Mccalla, "Smart recommendation for evolving e-learning system," *11th International Conference on Artificial Intelligence in Education, Workshop on Technologies for Electronic Documents for Supporting Learning*, pp. 699-710, 2003.

[4] K. Papanikolaou and M. Grigoriadou, "Towards new forms of knowledge communication: the adaptive dimension of a web-based learning environment," *Computers & Education*, vol. 39, pp.333-360, 2002.

[5] C. M. Chen, H. M. Lee and Y. H. Chen, "Personalized e-learning system using item response theory," *Computers & Education*, vol. 44, no. 3, pp. 237-255, 2005.

[6] C. M. Chen, C. Y. Liu and M. H. Chang, "Personalized curriculum sequencing using modified item response theory for web-based instruction," *Expert Systems with Applications*, vol. 30, no. 2, pp. 378-396, 2006.

[7] C. M. Chen, "Intelligent web-based learning system with personalized learning path guidance," *Computers & Education*, Article in press, 2007.

[8] J. T. D. Yang, P. T. Yu, N. S. Chen, C. Y. Tsai, and C. C. Lee, "Using ontology as scaffolding for authoring teaching materials," *International Journal of Distance Education Technologies*, vol. 3, no. 1, pp. 81-96, 2005.

[9] S. J. H. Yang, I. Y. L. Chen and N. W. Y. Shao, "Ontological enabled annotations and knowledge management for collaborative learning in virtual learning community," *Journal of Educational Technology and Society*, vol. 7, no. 4, pp. 70-81, 2004.

[10] M. Song, I. Y. Song, X. Hu, R. B. Allen, "Integration of association rules and ontologies for semantic query expansion, " *Data & Knowledge Engineering*, vol. 63, no. 1, pp. 63-75, 2007.

[11] C. Brewster, K. O'Hara, "Knowledge representation with ontologies: Present challenges—Future possibilities," *International Journal of Human - Computer Studies*, vol. 65, no. 7, pp. 563-568, 2007.

[12] H. J. Zimmermann, Fuzzy Set Theory and Its Application, Kluwer Academic, 1991.