Frame Based Intelligent Tutoring System with Weighted Attributes and Adaptive Hypermedia

Dr. N.Ch. Sriman Narayana Iyengar
School of Computing Sciences, VIT University, Vellore, TN, India
nchsniyr@gmail.com

***Abstract*- In this paper, we present an adaptive tutoring system for students of multiple domains with a web-based interface for flexibility. The displayed media is adapted according to the student's capability and aptitude by evaluating the student according to historical data and quizzes. The media is divided into dynamic frames and content of each frame is displayed adaptively. A weighted approach is used to evaluate the student capability and frames are generated based on a beta distribution. Initial evaluation of the system based on a paper simulation showed encouraging results.**

***Keywords*- Adaptive hypermedia, Bayesian networks, tutoring systems.**

I. INTRODUCTION & BACKGROUND

Intelligent Tutoring Systems are a type of educational systems [6] which consider user abilities and aptitude to adapt the content being learnt accordingly. ITS consider various factors involving user skill and knowledge level to display appropriate content which suits the user level. This can be done using various computing techniques like neural networks, Bayesian networks, conceptual lattices [16] and other fuzzy concepts [17] to map subject content to the user model. Moreover, the advent of the WWW has given rise to a wide range of Web based ITS [7] which use innovative methods of tutoring and a standard web interface as the client. These, combined with Adaptive Hypermedia [4, 5, 6, 7, 9, 17] which generates web content dynamically, offer the student a greater sense of freedom and a more effective learning experience. Another factor to be considered is the hypermedia content, which needs to be effective, adaptable and flexible. For this, we need a special authoring tool [8] which would allow for categorizing and giving weights to content, along with providing different types of media for learning, to cater to the needs of the system's mathematical model. Moreover, most ITS [3] do not take anomalous situations into consideration, which make them ineffective in extreme cases.

Another problem with most ITS is that they adapt user content in the next module and the current content being displayed is not reviewed with respect to the level of understanding achieved for the current module[3]. Hence, the user goes forward without understanding the current module, though future content displayed might suit him.

Hence, in addressing the above problems we propose a web based e-learning system with adaptive hypermedia and flexible content authoring. The system's main functionality would be to adapt and dynamically change content according to the user ability and the subject domain. The subject domains are going to be categorized into specific types and a new module in the system can choose one or more categories which relate closely to it and the overall character of the module is generalized by our expert system accordingly. Each user can be given some specific characteristic weights. The weights can be updated as the user uses the system and the subject content can be modified according to the result of processing the user weights and subject weights together to find the user's aptitude for the specific subject domain. A content authoring system is provided which has an option of including various types of multimedia like text, animation, audio and video. Animation creation tools and support for external Flash animations would be included. The module author would assign weights for each section in the module according to specific criteria and the expert system would automatically change this content according to the user's domain-normalized weights. There would be short adaptive quizzes in between to analyze the user's understanding and the content is modified accordingly so that the users can go at their own pace of study. All data generated by the system is stored for future analysis of the user when he subscribes to another module. The users can also interact with the module author and other users learning the module, to enhance their learning experience.

II. ORGANIZATION

The paper is structured as follows. In section 3 we characterize the representation of the subject model and the user model that is going to be used. Next in section 4, we describe the mathematical model used for generating adaptive content and making the system intelligent. Section 5 discusses the system architecture proposed. Section 6 shows the method of simulation employed. Finally, in 7 we give conclusions and proposed future work.

III. CHARACTERIZATION

The mathematical model of the system has been designed in such a way that attributes can be removed and added into the system flexibly and there are no fixed and static attributes that need to be proposed for the success of the system. Hence, an initial characterization of the attributes is done, but the characteristics of a subject domain are not limited to the characteristics given and the system can be modified as per the requirements.

A. Subject Domain Characterization

All possible domains are first divided into some generic prototypes with distinct characteristics so that the module author can build his module upon these characteristics. This would let the expert system understand the type of subject that is being authored, which would let it modify the content according to individual user profile.

For example the subjects can be divided into distinct characteristics like

- Analytical
- Memorization
- Technical aptitude
- Prerequisites needed
- Creative thinking

Each of the characteristics is given a weight and for each module, the quantization of the characteristic can be provided by the module authors based on their personal estimate.

B. User Domain Characterization

Similarly users too are given a quantified value for each characteristic proposed, which include all the subject characteristics and some subject independent characteristics like

- Concentration stamina
- Type of media preferred (audio/video/ text/images) in learning

These characteristics are taken into consideration too, in evaluating localized weights and generating dynamic content that needs to be displayed to the user.

IV. MATHEMATICAL MODEL

The course content consists of subjects which are categorized into modules which are further divided into frames. The organization of the course material can be thought of as a network of wired nodes wherein the reader should be taken from the starting frame of the module(start node)to the final frame(destination node) through the best suited course material for the user. The course material displayed to the user shall be personalized with respect to user character to enable him learn the subject in the most effective way and in the shortest possible time. The user shall be directed to the next frame by his performance in his current frame and his past historical performance data. The organization of the course material or the movement of the user in the network of the course can be categorized into a 2 dimensional layer system Figure 1. where the horizontal dimension would represent the progress of the student and the vertical dimension would represent the difficulty level of the frame.

Quiz

On completion of a group of frames, the user shall be given a quiz consisting of a variety of questions specially designed to test the student on various aspects. The quiz would have multiple

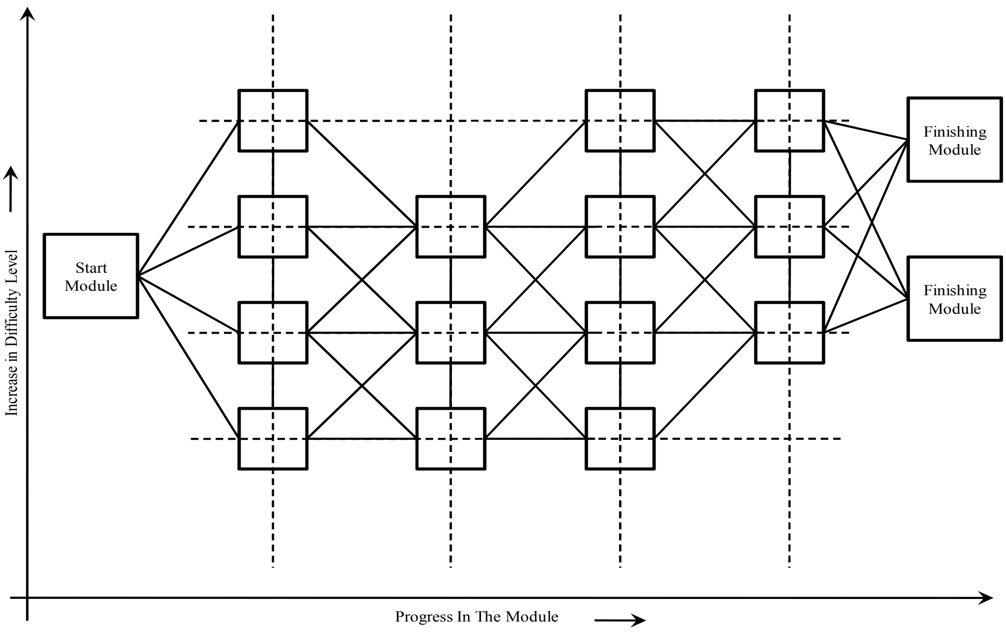

Fig.1 Frame Network

choice questions with each choice is made to absorb the student's understanding level as much as possible.

The student's understanding shall also be judged based on the incorrect options given by him/her. The questions of the quiz have been carefully designed on various parameters such as difficulty level, relevance etc. The quiz shall also contain some dummy/trap questions to judge the student even better. The author while entering the questions shall be asked to mention the difficulty level of the question.

Quiz Evaluation

The student is evaluated based on both his choices of correct as well as incorrect answers so as to have a better understanding of the student's learning level. According to the type of question, the author gives weights to the various attributes related to that question. The answer given by a student to each question is evaluated in terms of those attributes. The first question is generated based on the student's initial status. Once the student has attempted the question, the next question is chosen from the bank on the basis of his answer to the previous question (Figure. 2) i.e. local evaluation. Simultaneously histograms are drawn for each answered by the student with the attributes taken along the x-axis and student's score with respect to each of those attributes in the particular question along the y-axis Figure 3.

After the completion of a quiz the attribute-wise equalization of the histogram is done so as to draw one final histogram which is representative of the student's performance in the quiz Figure 4. The equalization is done so as to avoid the effect due to low finite sample

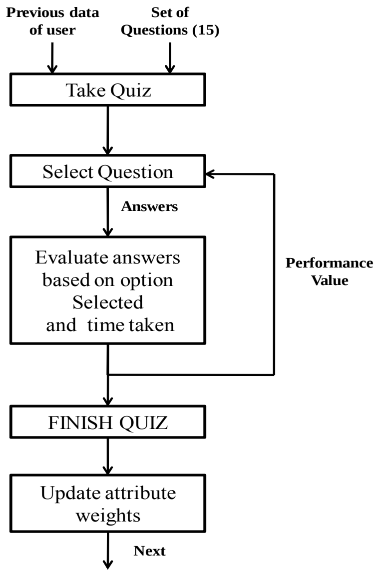

Fig.2 Question Generator

breakdown point [2] i.e. a student's performance in once particular question should not have a drastic effect on his overall performance. These histogram values are then used to update the student's overall performance attributes.

Dynamic Updating Of Difficulty Levels

The initial difficulty levels are given to the questions by the author of the quiz. These levels can then be updated dynamically based on the number of students answering them correctly or incorrectly. As we know normal distribution is one of most widely implemented distributions in real world scenarios. Hence based on the number of students and the way the question is answered by them, a graph can be plotted by taking various samples which shall be very close to a normal distribution curve [2]. Hence the question that majority of students fail to answer is updated to the next difficulty level. The equation for normal distribution can be given by:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left\{\frac{-1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right\}$$

where 'x' represents the number of students attempting the question. Based on the student's performance in the quiz the decision about the next frame that is most suitable for the student is taken. Similarly the overall performance of the student in the complete frame can be found by equalization of all the histograms drawn at the end of each test.

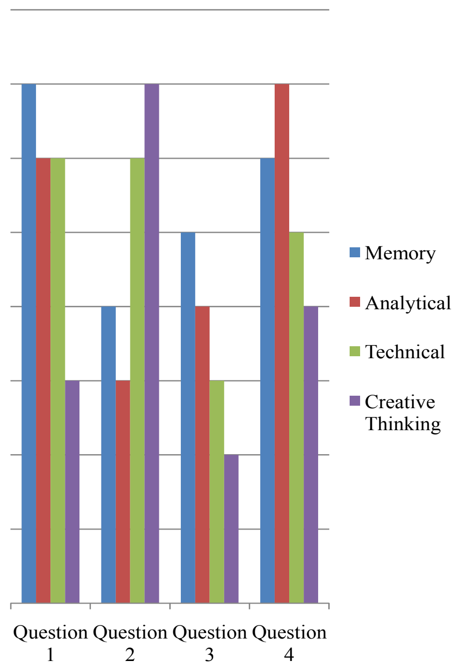

Fig.3 Question-wise performance histogram

The interpolation of the overall performance curve can let help us calculate the expected performance of the student before starting the module.

Evaluation of weights

The student and the subjects are evaluated based on certain attributes. The student attributes are categorized into two classes, subject specific, which are the same as the attributes of the subject, and subject independent attributes. The subject specific attributes can be memory, analytical skills, technical skills innovativeness and prerequisites needed. For students, attribute values measure the student's quantified skill in those attributes while for the subjects the attribute values represent their importance towards learning of the subject effectively. The subject independent attributes have been assigned global values for all students. All these values are dynamic in nature and would change based on future performance.

Calculating current weight

Subject Specific Attributes: $\{S_1, S_2, S_3, S_4, S_5, S_6, S_7 \ldots S_n\}$

Non Subject-Specific Attributes: $\{B_1, B_2, B_3, B_4 \ldots B_m\}$

Student attributes set: $\{a_1, a_2, a_3, a_4, a_5, a_6, a_7 \ldots a_n\} \cup \{b_1, b_2, b_3, b_4 \ldots b_m\}$

Subject attributes set: $\{s_1, s_2, s_3, s_4, s_5, s_6, s_7 \ldots s_n\}$

Global Value Set: $\{g_1, g_2, g_3, g_4 \ldots g_m\}$

S_is stand for the subject specific attributes while the B_is stand for the non-subject specific attributes

g_i's stand for the global weight assigned to the non-subject specific attribute.

b_i's are the values assigned to the non subject specific attributes while a_i's stand for the values of the subject specific attributes, for the students. s_is stand for the importance values of the various subject specific attributes for the particular subject.

$$\text{Weighted Average (W)} = \frac{\sum(aisi) + \sum(bigi)}{\sum si + \sum gi}$$

This is considered to be the student's status just before starting the module.

Adaptive Frame Generation

1). Initial model: Initial models that have been made are static in nature and do not allow much flexibility. Some models increase the difficulty level of the modules as the studentprogress considering the current performance of the student in the course so far and whether the student is ready for the next topic [4]. The previous models are abstract in nature and do not consider the fuzziness that comes into play when humans are taken under consideration. We need to judge the student on the basis of his mental abilities in the particular topic rather than the standard he is studying in, and also asses him continuously so as to understand the student's interaction with the subject. We need to consider the student's performance in both the global as well as local sense. The assessment scheme should also be immune to low finite sample breakdown point[2]. In this model every frame is given attributes same as that of the subjects and a net weight for the frame is calculated based on its contents. The student's rank is calculated as above.

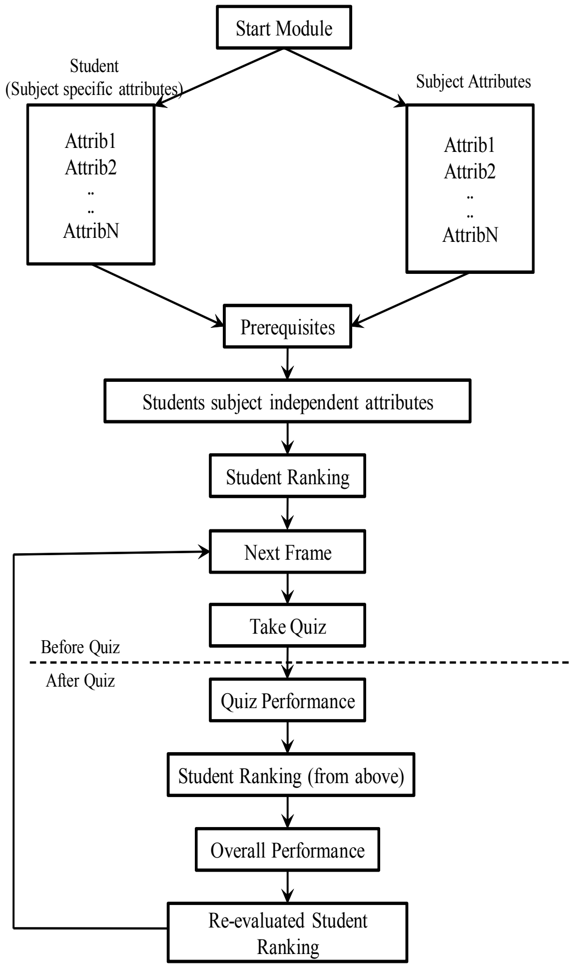

Fig.5 System Flow Chart

In this model every frame is given attributes same as that of the subjects as mentioned above and a net weight for the frame is calculated based on its contents. The student's current weights are calculated as above. We have frames that consist of the same content in terms of topics covered, definitions but vary in their weight values due to the difference in their difficulty levels. Each frame has an order id to maintain the continuity in the course. Once the student has completed going through the frame he is presented with a quiz. Each question in the quiz is also assigned a weight based on various parameters such as difficulty level and relevance. Based on the performance in the various parts of the quiz the student's weights are updated using the weights of the questions. The updated weight of the student is then compared with those of the frames available next in order. The one closest to the student's weight is selected and displayed to the student.

The previous models did not perform as well as expected as they did not take into consideration the students' history and the overall performance while evaluating them. There can be situations where the student might show extraordinary performance both in the positive as well as negative direction. Such performances should be given least importance as they do not represent the student correctly. Such data when used for evaluating a student can act as noise and might give us a wrong perception of the student.

2).Experience Model: Taking the shortcomings of the previous models into consideration and accounting for the proposed architecture of the course material we propose a new model which, apart from taking into account the student's initial status before starting the module, the student's performance in the module, also takes into account the student's past performances and the way student has been going through the module (has been forwarded in the frame network) so far, to decide and dynamically choose the following material best suited for him. We make use of the well known β-distribution for the same. The model goes as follows.

Let us assume that the student's rank as evaluated above is 'W_i' before going through the frame. After having gone through the frame and attempting the quiz the student's rank is re-evaluated to 'W_f'. Now we consider the change in the student's rank and call it the growth factor (G_f).

$$G_f = (W_f - W_i)$$

Let **T** be a threshold value used to assess the student's growth rate. We consider three cases which are explained as follows:

- $G_f > T$ (Significant growth)
- $-T < G_f < T$ (The student is more or less consistent)
- $G_f < -T$ (Significant drop in performance)

All the above three cases eventually end up with two choices amongst which one is chosen using beta distribution. To make things clearer following is the explanation for the first case.

If the student's growth rate is greater than the threshold value T, we can infer that the student is capable of a higher difficulty level and should be moved to the next higher layer. The same can be done in two different ways i.e. the student can either be shown the same content with a few higher level concepts i.e. the student is moved a step up along the same vertical layer or the student can be taught the next upcoming topics with the higher difficulty level i.e. to move the student to the next frame in order in the next difficulty level. The choice of which one amongst the two is most appropriate is done using the beta distribution. As we know beta distribution is used as a prior distribution for binomial proportions in Bayesian analysis [13]. We map beta distribution to our analysis as follows. Beta distribution is given by

$$F(x;\alpha,\beta)=\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\,\Gamma(\beta)}\,(x^{\alpha-1})\,(1-x)^{\beta-1}$$

As in Bayesian analysis the terms α and β mean the number of times heads and tails appeared in the previous n trials of tossing a coin, here α and β mean the number of times the choice one and choice two have been made in the n previous frames respectively. The choice one and choice two being the two choices we were eventually left with as explained above. The value of the function gives us the probability distribution of the random variable representing the probability of getting head/choosing choice one, given that in the previous n frames α times choice one was preferred while β times choice two was preferred. Now we find the value of x (say p) for which the above function assumes the maximum value. Now the choice is made as follows:

If $p > \frac{1}{2}$, choice one is taken else choice two is taken.

Therefore it can be seen than beta distribution takes into account the way in which the student has been going through the module so far i.e. the student's progress till then, to decide the next most suitable frame for the student. Hence the choice of this distribution is justified.

For the second case where the user is consistent the user is either forwarded to next frame in the same difficulty level or is shown the same content but with a few advanced concepts i.e. moved up along the same vertical layer. In the third case the two choices are either the student is shown the same content with more explanations i.e. moving a step down in the same vertical layer, or the student is taken to the next frame in order in the lower difficulty level. This is how the student learning goes through the network of frames, every frame forwarding the student to the next most suited frame and eventually reaching the destination i.e. the completion of the module

The system is highly adaptive and records every move of the student to develop an understanding with the student. The students can perform considerably bad because of bad health or can also perform extraordinarily well by taking the help of an expert which would mislead the system. Such extreme performances of students due to anomalous conditions are taken into account using a suitable clustering algorithm can be employed such as PCA (Possibilistic Clustering Algorithm). As the system is designed for humans it can be safely assumed that none of the attributes of the student shall change enormously in a small period of time and hence if it does change by an inhumanly large amount the data should be ignored as it does not give us the right information about the student. PCA forms clusters based on each attribute and hence an unacceptably high change in even a single attribute of the student is recorded and the complete data set is removed. Once the clusters have been formed the values that do not confirm to any of the respective clusters are called outliers and are hence ignored. Hence PCA monitors these extreme circumstances and removes them from the database. The outlier values that do not confirm with the cluster are neglected and the values present in the cluster are used to judge the overall performance.

V. SYSTEM ARCHITECTURE

The system would be completely web-based for easy content delivery and scalability. The Server is programmed in Java using the free Google Web Toolkit libraries. All user attributes and metadata are stored in a common RDBMS for fast retrieval, but however, the academic content is stored in the form of XML files for easy backup and retrieval and automatic parsing. The Client would be any of the popular web browsers, either over a local network or the internet. The audio and video content would be embedded in the form of XML tags and would later be converted into appropriate JavaScript for rendering by the browser.

However, our system is not limited to this particular architecture and is quite flexible to be implemented in other architectures, assuming the mathematical model can be accommodated without any significant changes. Embedding such a system into any existing application based tutors is possible.

VI. SYSTEM EVALUATION

The system evaluation was done by writing an intelligent tutor based on the system proposed, mainly by using the Google Web Toolkit (GWT), using client-server architecture. The system mainly contained an authoring module for the teachers and a learning module for the students.

TABLE1
RESPONSES INTERPRETATION FOR STUDENT QUESTIONNAIRE (28 RANDOM USERS)

Question	Response	Response Inference
How was the second system in terms of difficulty of content over the first one?	4.2 (Rated over a scale of 5.0)	Students of all abilities were given content of difficulty appropriate to their skill.
Were you given a particular concept again on non-grasping of it earlier, with an easier to understand material?	71.4% answered Yes	Students learn the whole subject without skipping concepts that they do not understand.
Would you like to use such a system for most of your e-Learning?	82.14% answered Yes	Students intuitively want such a system for all their courses

VII. CONCLUSION AND FUTURE WORK

In this paper, we presented an intelligent tutoring system which is web-based and has adaptive hypermedia. We mainly emphasize on the student evaluation aspect and the adaptivity of the content in the system according to the student needs. A beta distribution model and possibilistic clustering approach algorithm were used to evaluate the user. A manual evaluation of the system shows that it is clearly a much more effective and faster approach in learning content than standard tutoring systems which have non adaptable content.

Our future work would be on improving our system to be more effective by using better prediction models, more attributes for evaluation and improved content display mechanisms to include better animations and more flexibility in the multimedia. Another idea is to make the frame traversing a 3 dimensional one, improving upon the current 2 dimensional traversing. We also have a proposal of dividing the frames into individual entities (i.e fragments of text and each image would be treated similar to frames in the current system).

REFERENCES

[1] Nian-Shing Chen, Kinshuk, Chun-Wang Wei and Hong-Jhe Chen, (2006)" Mining e-Learning Domain Concept Map from Academic Articles", Proceedings of the Sixth International Conference on Advanced Learning Technologies

[2] Rand.R.W.Wilox, Fundamentals Of Modern Statistical Methods, Springer publications.

[3] Anandi Giridharan , P. Venkataram, "A Design of Subject Model for Web-based Education System", IEEE proceedings 2002

[4] Victor Manuel García-Barrios," Adaptive E-Learning Systems: Retrospection, Opportunities and Challenges,28th international conference interfaces ITI 2006, June 19-22,2006.

[5] Francesco Colace, Massimo De Santo, "Adaptive Hypermedia System in Education: A User Model and Tracking Strategy Proposal", 37th ASEE/IEEE Frontiers in Education Conference October 10 – 13, 2007, Milwaukee, WI

[6] Zurida Ishak, Muhammad Rafie Mohd.Arshad, Puhtra Sumari, "Adaptive Hypermedia System in Education: review of available technologies," ICICS-PCM 2003 15-18 December 2003Singapore.

[7] Ioannis Hatzilygeroudis, Christos Giannoulis & Constantinos Koutsojannis," Combining Expert Systems and Adaptive Hypermedia Technologies in a Web Based Educational System", Proceedings of the Fifth IEEE International Conference on Advanced Learning Technologies (ICALT'05).

[8] Alexandra I. Cristea and Arnout de Mooij," Designer Adaptation in Adaptive Hypermedia Authoring",Proceedings of the International Conference on Information Technology: Computers and Communications (ITCC.03).

[9] M´aria Bielikov´a and Jaroslav Kuruc," Sharing User Models for Adaptive Hypermedia Applications" Proceedings of the 2005 5th International Conference on Intelligent Systems Design and Applications (ISDA'05).

[10] Oliver Bohl, Dr. Jörg Schellhase, Ruth Sengler, Prof. Dr. Udo Winand," The Sharable Content Object Reference Model (SCORM) – A Critical Review", Proceedings of the International Conference on Computers in Education (ICCE'02).

[11] Aasim Zafar, Nesar Ahmad, "Towards Adaptive e-learing: Technological Challenges and Enabling Technologies", e-Learning Research Agenda Forum-2004

[12] David Heckerman," A Tutorial on Learning With Bayesian Networks", Microsoft Research, Advanced Technology Division, Microsoft Corporation.

[13] R. Krishnapuram, J.M. Keller,"A possibilistic approach to clustering", IEEE Trans. Fuzzy Syst. 1 ,1993,pp. 98–110.
[14] Alexandra Cristea, Department Of Mathematics and Computer Sciences, "Adaptive Hypermedia", Eindhoven University Of Technology.
[15] D.Driankov, H.Hellendoorn, M.Reinfrank,"An Introduction to Fuzzy Control", Narosa Publishing.
[16] Luciano Silva, Denise Stringhini, Pollyana Notargiacomo Mustaro, Ismar Frango Silveira, "Adaptive Learning through Conceptual Lattice-based SCORM Meta-Objects",IEEE Trans.
[17] Antonina DA'ITOLO, Vincenzo LOIA," A Fuzzy approach to Adaptive Hypermedia", Fourth International Conference on knowledge-Based Zntelligent Engim'ng Systems 6 Allied Technologies, 30" Aug-I" Sept 2000, Brighton,UK