Computational Intelligence in Adaptive Educational Hypermedia

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Abstract- In this paper neuro-fuzzy synergism is applied to implement content sequencing in adaptive hypermedia systems. The level of understanding of the learner is used to construct lessons adapted to the learner's knowledge goals and level of expertise on the domain concepts s/he has already studied. The learner's evaluation is based on defining appropriate fuzzy sets and relate learner's response with appropriate knowledge and cognitive characterizations. A connectionist-based structure of the domain knowledge is adopted for representing knowledge and inferring the planning strategy for generating the hypermedia page from pieces of educational material. The fuzziness associated with the evaluation of the learner is handled well by the proposed connectionist architecture.

1. Introduction

Adaptive educational hypermedia systems have instantiated a relatively recent area of research integrating two distinct technologies in computer assisted instruction, Intelligent Tutoring Systems (ITS) and Hypermedia Systems. This is in effect a combination of two opposed approaches to computer assisted learning: the more directive tutor-centered style of traditional AI based systems and the flexible learner-centered browsing approach of a hypermedia system [5]. The attraction of hypermedia for education purposes lies in their ability to actively engage the learner in the acquisition and use of information, to support multiple different instructional uses (tutoring, exploration, research, etc.), to support different learning styles and to promote the acquisition of different representations that underlie expert-level reasoning in complex, ill-structured domains [17].

However, in practice, several problem are encountered: (*i*) it is unlikely all learners to be equally suited to performing their own sequencing, pacing and direction, (*ii*) the knowledge of different learners on the subject being taught can vary greatly (different knowledge background), while it may grow differently through the interaction with the system, *(iii)* learners tend to get lost, especially when the corpus is large and/or learners are novices to the domain presented, *(iv)* learners, when browsing, may fail to get an overview of the how all the information fits together and *(v)* in the absence of information that might help them formulate goals and find relevant material, learners may stumble through the corpus in a disorganized and instructionally inefficient manner, *(vi)* the learner is not always going to choose what information to see next in a way that will lead to effective learning.

The introduction of adaptivity into the educational hypermedia systems aims at providing the system with the ability to change dynamically according to the changing learner's needs. Two methods are generally proposed in the literature for implementing adaptation in these systems: adaptive presentation (or content sequensing) and adaptive navigation (or link-level adaptation) [3]. In the first case the content of a hypermedia page is generated or assembled from pieces of educational material according to the learner's knowledge state [16], while in the second case altering visible links to support hyperspace navigation is suggested [19][22]. In this paper we propose a neuro-fuzzy approach to implement content sequencing. The goal is to adapt the content of the page supplied to the particular learner's knowledge level, goals and preferences. In this way the navigation space is restricted in order to protect (especially novices) learners from information overflow.

2. Approaches to implement adaptivity in educational hypermedia

In this section, we briefly present related work on some important factors influencing the system's adaptivity, such as the *domain model*, the *modeling of the learner* and the *instructional approach*.

In hypermedia systems the structure of the knowledge domain is usually represented as a semantic network of domain concepts, or generally elementary pieces of knowledge for the given domain, related with different kinds of

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links (see [3] for a review on these systems). Learner's knowledge is most often represented by an *overlay model*, [3], which is based on the structural model of the subject matter. The idea of the overlay model is to represent an individual learner's knowledge of the subject as an "overlay" of the domain knowledge. For each domain concept, an overlay model stores some value (binary/qualitative measure/ probability), which is an estimation of the learner knowledge level of this concept. Overlay models are domain independent and flexible and were originally developed in the area of ITS and learner modeling (for a review on ITS see [23]). A different approach is to use a *stereotype model* to represent the learner's knowledge. A stereotype learner model distinguishes several typical or stereotype learners, so for each dimension of learner modeling the system has a set of possible stereotypes, and a particular learner is usually modeled by assigning him to one of stereotypes for each dimension of classification. Finally, the pedagogical knowledge incorporated in the system affects its adaptivity and effectiveness. This type of knowledge supports didactic decisions and implements the tutoring strategy of the system, which is responsible for deciding how to sequence knowledge in order to achieve instructional goals and for selecting a particular activity relevant in the current context. Various instructional strategies such as traditional tutoring, cognitive apprenticeship, coaching, Socratic dialogue, negotiated tutoring have been implemented in several ITS [21] [12] [20].

3. The neuro-fuzzy approach

In this section, methods from computational intelligence are proposed to address several key points that affect the effectiveness of an adaptive educational hypermedia: the structure of the domain knowledge, the instructional planning and the evaluation of the learner knowledge under uncertainty.

The proposed approach is based on two types of knowledge: *(i)* knowledge about the domain being taught, which is represented in by a connectionist network, and *(ii)* knowledge about the learners, which is represented in the form of fuzzy logic-based learner modeling. The domain model serves as a basis for structuring the content of an adaptive lesson and is based on the domain concepts and the knowledge goals of the course. A connectionist network, with nodes corresponding to domain concepts and weighted connections reflecting relationships between concepts serves to model the domain (see Figure 1). For each domain model concept, an individual learner's knowledge model stores some qualitative characterization, which is an estimation of the learner understanding of this concept (see Figure 2). Learner actions (e.g. HTML page visits, problem solving, quiz answering) are tracked and used to evaluate knowledge levels for involved concepts. In this way, a hypermedia educational system may be adapted in three ways: *(i)* adapt the lesson presentation according to the current learner's level of understanding and knowledge goals, *(ii)* update the learner model in the light of evidence gathered during interaction with the system and *(iii)* further improve its tutoring performance by exploiting the training and generalization capabilities of the artificial neural networks to extract information from learner profiles that contain a true picture of the possible knowledge levels of the learners and of the possible learning paths.

This approach is especially useful for planning the content in a distance learning course through the Web [11]. In distance learning, the target group is characterized by a considerable heterogeneity concerning learners background knowledge, experiences, cultural backgrounds, professions, motivations and goals. The restriction of the domain knowledge seems the most appropriate aid in order to support the learners in their first steps. To this end, both *content sequencing methods*, which help to restrict the domain knowledge according to the learner's level of understanding, and *simulations* that act as cognitive tools implementing an experimental environment where the learner can test his/her knowledge and experiment under different conditions, [6], are used.

3.1 Representing knowledge by a connectionist network

An important issue in the development of a educational system, which will be capable to support pedagogical decisions is to provide various types of educational material on the same knowledge [7]. As a first step towards this direction we constructed the domain knowledge in the three layers of a connectionist architecture, as shown in Figure 1, with each layer providing a different type of pedagogical information. The architecture is based on the notion of knowledge goals that learners willingly adopt, in an attempt to provide a way for learners to control the environment in which they learn. In addition, it gives them the opportunity to select the next knowledge goal according to their educational needs. To this end, in the first layer of the connectionist network the knowledge goals are defined, while the second layer consists of clusters of the domain concepts related to the goals. In the third layer, the educational material related to each concept is represented in different classes, such as text, images, simulations, examples, solved and unsolved-exercises and so on. A specially designed dynamic neural network for each goal, named Relationships Storage Network-RSN [14], is used. The RSN performs associate inference and, unlike the general use of an associative memory, it operates synchronously: *(i)* it updates the states of its nodes simultaneously, and *(ii)* the input pattern is kept unchanged until convergence of the network. Patterns of relationships among concepts implement different strategies for planning the content of the selected knowledge goal (see [11] for details). A planning strategy is represented by a collection of *m* patterns defined on $\{-1,1\}^n$ and is stored in the RSN using a storage algorithm that utilizes the *eigenstructure method* and guarantees that the patterns of relationships are stored as asymptotically stable equilibrium points of the RSN [13].

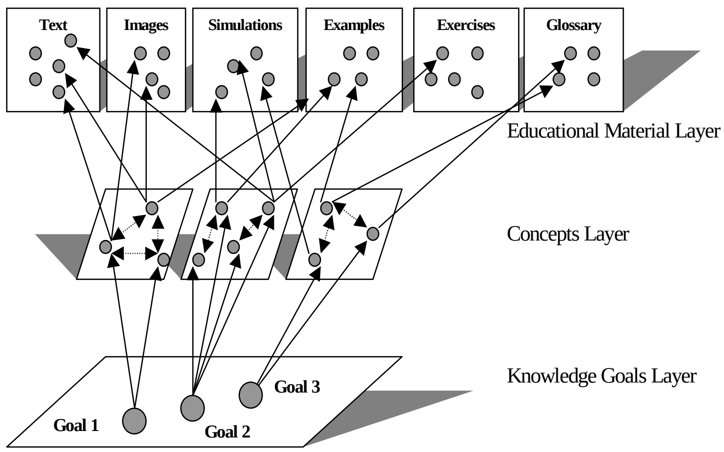

Figure 1. The connectionist-based structure of the domain knowledge of the course.

In the third layer the educational material related to each concept is organized in categories, such as text, diagrams and images, examples, simulations, solved-exercises, unsolved-exercises and so on. Weights connecting the second and the third layer are unique for each concept and each concept may be associated with several categories of educational material. The educational material is then joined under a predefined form of presentation to generate a course. The development of the educational material was influenced by Bloom's idea of various kinds of learning outcomes [2]. Bloom identified six levels within the cognitive domain, from the simple recall, or recognition of facts, as the lowest level, through increasingly more complex and abstract mental levels, to the highest order, which is classified as evaluation. Following this approach, the knowledge recall and the comprehension level are supported in our system by text and images, the knowledge application and the analysis level by examples, and the synthesis and evaluation level by simulations and case studies. In addition, solved-exercises, in the form of self-assessment tests, accompany the educational material related to the knowledge application, analysis, synthesis and evaluation levels, in order to introduce general methodologies that address specific categories of problems.

3.2 Evaluating learner's level of understanding

In [2] Bloom proposed a taxonomy of intellectual behavior important in learning, which includes three overlapping domains: the *cognitive*, the *psychomotor*, and the *affective*. Through the cognitive system, the learner perceives, stores, processes, and retrieves information so adopting Bloom's taxonomy on the cognitive domain we can result in a form of evaluation of learner's *level of understanding*. Thus, learner's evaluation on the concepts that s/he has studied is based on two types of information: answers to questions that evaluate the cognitive domain and measurements that evaluate the affective [6][10]. In both cases, several factors contribute to uncertainty in the evaluation procedure, such as careless errors and lucky guesses in the learner's responses, changes in the learner knowledge due to learning and forgetting, and patterns of learner responses unanticipated by the designer of the learner model. Thus, the development of an accurate model for evaluating the learner's understanding is based on uncertain information.

Different types of questions define the relations and properties of a concept, or a group of concepts that are relevant to specific learning outcomes that we aim to identify. Educational material related to higher order learning outcomes will be supplied to the learner if his/her answers to the lower ones have been evaluated as *sufficient*. An important issue in the construction of such questions is the content of the answer. Various types of questions organized in categories as proposed in [11] can be used, e.g. multiple choice, fill-in-the-blanks, boolean, multiple correct answers, each one having a different weight representing its importance in the evaluation procedure [1]. For example, in the distance learning course offered by our Department, entitled *"Introduction to Computer Science and Telecommunications"* [4] [7][11], identifying the learning outcome of comprehension regarding the concepts *data link layer, network layer, session layer* is performed using questions like the following:

Which of the OSI layers handles each of the following;

1. *Breaking and transmitting bit stream into frames.*
2. *Determining which route through the subnet to use.*
3. *Providing synchronization.*

In the above question, the knowledge of the multi-layer structure of the OSI model must be recalled and tested for comprehending the functions undertaken by each layer of the OSI model.

Several measurements are recorded from the learner-educational program interaction and used for evaluating the learner's awareness, interest, attention, concern, and responsibility factors, which are related to the affective domain: the number of questions and exercises that the learner tried to answer or solve, the points scored, the number of learner attempts before giving the correct answer, the frequency of the encountered misconceptions, the number of repetitions of a topic by the learner, the time s/he spends for self-assessment, the type of information the learner prefers (text, pictures, sound, video, simulations, URLs) and how often s/he navigates through the HTML pages of the educational material supplied for a knowledge goal. These measurements are further used to identify affective learning outcomes.

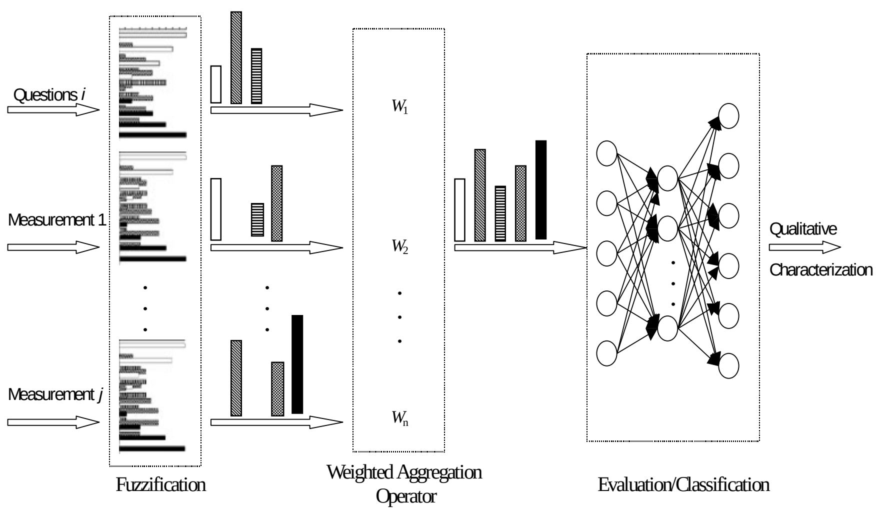

Figure 2. The three stages of the evaluation procedure.

Thus, by analyzing the learner's answers and by processing the various measurements conducted by the system, it is possible to trace: gaps in the knowledge of the learner, mistakes and misconceptions. To this end, a three stages neuro-fuzzy approach, originally proposed in [15] and extended in [8], is applied. The first stage fuzzifies inputs that contribute to the evaluation of the level of understanding, based on the estimations of experts to the degree of association between an observed input value (in our case we apply a discretization of the universe of discourse) and the learner's knowledge on this concept. Depending on the input, a fuzzy subset is generated for each measurement or answer contributing to the evaluation. The next stage realizes a fixed weight aggregation network, utilizing the union operator, that processes these fuzzy subsets. The network weights are evaluated using the Saaty's method [16] and determine the importance of each preliminary decision in evaluating the learner's knowledge. A preliminary decision is expressed by a fuzzy subset relating a measurement or answer to the possible qualitative characterizations of the learner's understanding. The last stage consists of a backpropagation network that evaluates the level of understanding of the learner with regard to a concept by classifying him to one of the categories {EI, I, RI, RS, AS, S} = {Extremely Insufficient, Insufficient, Rather Insufficient, Rather Sufficient, Almost Sufficient, Sufficient}. This scale has been experimentally found to provide evaluation results closer to human teachers evaluation performance, when compared with previous work in the area [15][18].

Depending on the concept, the qualitative characterizations of the learner's understanding are converted to numeric values (fuzzy singletons), in order to feed the RSNs. Note that, when the learner's level of understanding with regard to a concept is characterized as Extremely Inefficient, a membership degree of approximately 1 is assigned to this concept. This means that the learner certainly has to study this concept. On the other hand, a small membership degree of approximately 0.1 is assigned when the learner's level of understanding on a concept is evaluated as Sufficient.

4. Application examples

Especially in the case of a distance learning course, where the target group is characterized by a considerably heterogeneity concerning their background knowledge, experience, cultural background, professions, motivations and goals, the content sequencing by restricting the domain knowledge seems to be the most appropriate aid in order to support learners. Therefore, we have tested the proposed approach in a Web-based hypermedia course [4] [7][11]. In all the cases below, the learner has selected the knowledge goal “ISO Architecture” and his performance has been evaluated differently concerning the various concepts he had to study. Note that this knowledge goal contains the largest number of concepts (26) among the 25 knowledge goals of the course [11].

In the first case, a learner exhibits performance which is characterized as “Rather Insufficient” with respect to the outcome concept *Physical layer* and as “Rather Insufficient” or “Almost Sufficient” to the prerequisites/related of that concept.

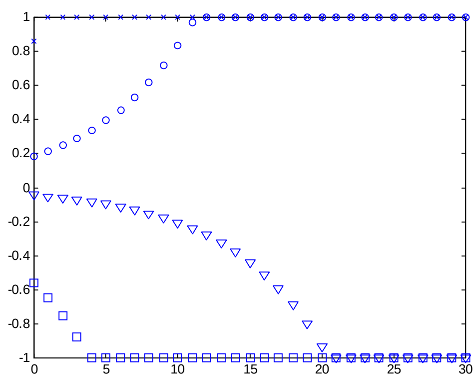

Figure 3. *Digital Transmission*: triangle, *Physical Layer*: x-mark, *Synchronization*: square, *Transmission Means*: o-mark.

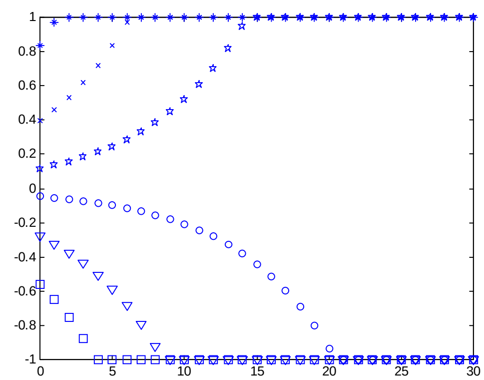

Figure 4. *Digital Transmission*: triangle, *Physical Layer*: x-mark, *Synchronization*: square, *Transmission Means*: o-mark, *Network layer*: pentagram, *Packet Routing*: *-mark.

From Figure 3 it is shown that the activity of the concept node that represents the prerequisite concept *Synchronization*, i.e. prerequisite to the outcome *Physical Layer*, goes to –1, which means that the node is deactivated and the educational material associated with this concept will not be presented. On the other hand, the activity level of the prerequisite concept *Transmission Means*, i.e. prerequisite to the outcome *Physical Layer*, goes to +1 and the material will be presented. Note that, after transformation to the interval (0,1), the activity level at cycle=0 indicates the result of the learner’s evaluation, which in the case of the *Synchronization* node is “0.26|Almost Sufficient” while of the prerequisite (to the outcome *Physical Layer*) concept *Transmission Means* is “0.58|Rather Insufficient”. Similarly, the concept node *Physical layer* is activated since the learner has been evaluated as “0.87|Rather Insufficient” in this outcome concept. Thus, following the recalled planning strategy the generated lesson includes all the concepts of the knowledge goal apart from the successfully studied prerequisite and related ones.

In the second case, a learner exhibits performance which is characterized as “Rather Sufficient” with respect to the outcome concepts *Network layer* and *Physical layer* (the rest of the outcome concepts have been successfully studied). The recalled planning strategy suggests that the generated lesson should include both the outcome concepts and their prerequisite/related that have not been successfully studied yet. From Figure 4 it is shown that the outcome concept node *Physical layer* is activated since the learner has been evaluated as “0.67|Rather Sufficient”. Also, the node that represents the outcome concept *Network layer* is activated although the learner has evaluated as “0,55|Rather Insufficient” as this is an outcome concept for the selected knowledge goal. On the other hand, the concept *Transmission Means*, prerequisite concept of the outcome *Physical Layer*, goes to –1, which means that the node is deactivated and the educational material associated with this concept will not be presented. The activity level of the prerequisite concept *Packet Routing*, i.e. prerequisite to the outcome *Network Layer*, goes to +1 and the material will be presented. Note that, the learner's evaluation, in the case of the *Packet Routing* node is "0.86|Insufficient" while of the prerequisite concept *Transmission Means*, *i.e.* prerequisite to the outcome *Physical Layer*, is "0.48|Rather Sufficient".

5. Conclusions

The method of content sequencing aims at minimizing the information overload of the learner by adapting the educational material provided to his/her background knowledge, experience and educational needs. The paper applies specialized connectionist-fuzzy architectures to the content sequencing in a hypermedia system. The proposed connectionist approach for representing domain knowledge facilitates the adaptation of the lesson to the learner's needs. A formulation of the planning strategy retrieval for selecting the content of a knowledge goal in the context of the dynamics of the connectionist network has been proposed. The evaluation of the learners is implemented by a qualitative level of understanding. However, the fuzziness associated with the evaluation of the learner's level of understanding seems to be handled well with the connectionist network.

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