The Use of Conceptual Maps in a
Hybrid Intelligent Tutoring System

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Abstract. *The integration of conceptual maps in a Hybrid Intelligent Tutoring System based on Artificial Neural Networks and Expert Knowledge is presented. Conceptual Maps are tools for knowledge representation and organization. The active manipulation of concepts is related to David Ausubel's Theory of Meaningful Learning. Empirical studies, comparison of three independent groups, have shown the statistically significant effect of the inclusion of conceptual maps. Two control groups are employed. In the first group, users navigate freely on the course contents. Intelligent content navigation without conceptual maps is employed to the second control group of users.*

Resumo. *A integração de mapas conceituais em um Sistema Tutor Inteligente Híbrido baseado em Redes Neurais Artificiais e Conhecimento de Especialista é apresentado. Mapas Conceituais são ferramentas para representação e organização de conhecimento. A manipulação ativa de conceitos é relatada pela Teoria de Aprendizagem Significativa de David Ausubel. Estudos empíricos, comparação entre três grupos independentes, mostraram efeito estatisticamente significativo da inclusão de mapas conceituais. Dois grupos de controle são empregados. No primeiro grupo, os usuários navegam livremente no conteúdo do curso. Navegação inteligente sem mapas conceituais é empregada no segundo grupo de controle.*

1. Introduction

The social dynamics of our present world leads people to continuous professional and personal development. The quality and form with which the learning process is taken can be decisive in obtaining the desired success by the majority of professionals. Distant learning is one of the most important paths in this complex and demanding con-juncture in order to promote learning. In this context, the area of Informatics in Education has contributed with intelligent tutoring systems (ITS) and Psychology, on the other hand, provides concepts and methods, such as conceptual maps and models of significant learning.

In this study, we present a web-based computational tool to realize the integration of conceptual maps into a hybrid intelligent tutoring system. Despite the fact that we have used a specific ITS implementation, the generalization to other approaches

is straightforward. Empirical experiments are conducted and their results are analyzed in order to validate our architecture. The comparisons of three independent groups have shown significant effect of the inclusion of conceptual maps. Two control groups are employed. The first group of users navigates freely on the course contents. Intelligent content navigation without conceptual maps is employed to the second control group of users. The third group is the experimental group and, therefore, has the same setup of the second group with the inclusion of conceptual maps.

2. Background

2.1. Conceptual Maps

Conceptual maps were introduced by Novak (1977) and are similar to semantic networks. However, instead of a logical knowledge structure, conceptual maps reveal the psychological knowledge structure [Wandersee 1990]. They are tools to organize and to represent knowledge, mainly with concepts usually formatted as circles or rectangles. The relation between concepts (or propositions) is indicated by a labeled line. The label for the majority of concepts is a word, but sometimes symbols are employed. Propositions are reports about some object or event of the environment. They encompass two or more connected concepts to build a meaningful sentence (see Figure 1).
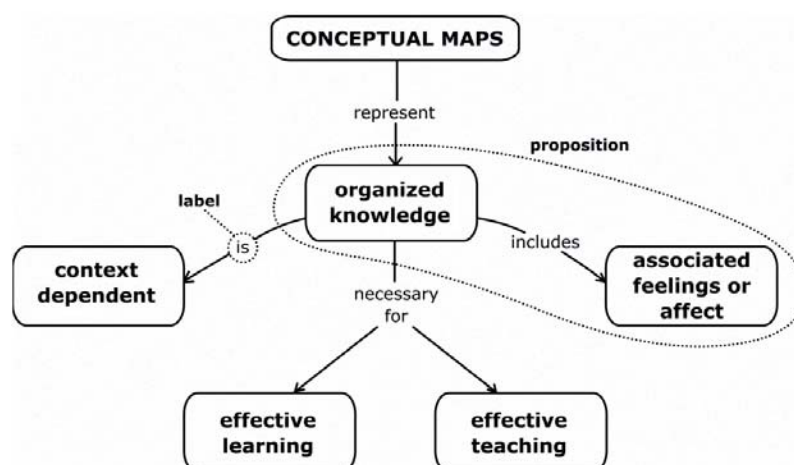

Figure 1. Fragment of a conceptual map about conceptual maps.

The process of "meaningful learning" reached by elaboration of conceptual maps implies the learning of grouping concepts with respect to their perceptive traces and categories, which possesses personal meanings. Ausubel (1978) states a fundamental assumption that meaningful learning occurs when new information is acquired by means of an intentional effort of the learner to connect it to preexisting concepts and propositions in his knowledge structure. Conceptual maps can be useful to the meaningful learning process because they give support at the identification of general concepts before the introduction of more specific concepts and serve as basis for chaining of learning tasks.

According to Ausubel, the organizational principles of conceptual maps put in evidence the pedagogical features of them. In the elaboration of concepts maps, concepts which are apparently similar to two people reveal explicit differences of

comprehension. This principle, called "Principle of Progressive Differentiation", presumes that general concepts are progressively specified. Theoretically, this principle is supposed to facilitate the meaningful learning since it is easier to understand differentiated aspects of a previously understood whole content rather than comprehend the whole content from its previously understood parts. In other words, the most general ideas of a subject should be presented first and then progressively differentiated in terms of detail and specificity. Instructional materials should attempt to integrate new material with previously presented information through comparisons and cross-referencing of new and old. The particular tracing that an individual does using contents from a specific discipline reflects his own hierarchical structure of knowledge.

Another principle stated by Ausubel is the "Principle of Integrative Reconciliation of the Cognitive Structure of Learning". Such a principle consists of emphasizing differences and similarities, real or not, that exist among concepts by showing the specific relations. This principle when it is pedagogically applied leads to the sequence programming of contents or, more specifically, in considering the order in which a subject could be presented to learners. The disrespect to this principle generates cognitive conflicts that will be harmful to conceptual learning [Amoretti 2003].

2.2. Artificial Neural Networks

The human brain, a neural network, is composed of neurons. The biological neurons are divided in three interrelated sections: i) the body of the cell, ii) dendrites and iii) the axon. The dendrites receive the nervous pulses (information) of other neurons, transmitting them to the body of the cell. Soon afterwards, the information is transformed in new pulses that are transmitted through the axon. The connection locus between the axon of a neuron and the dendrite of another neuron is called "synapse." The synapses work as valves, being capable to control the transmission of pulses (flow of information) among the neurons in the neural network. The effect of the synapses is variable and their plasticity implements the adaptation capacity of the neuron. Inputs are sensed by dendrites and affected by synapses (each one with its specific weight, gain value). The output is defined based on the sum of received stimuli and on the activation function that converts such information on the neuron activation level

Typically, an Artificial Neural Networks (ANN) has the following operation: after the specification of the structure (number of neurons, topology, neuron dynamics, training algorithm), a series of examples (training set) is presented to adjust ANN for their recognition and, more important, the generalization for unseen situations. The present work is based on multilayer perceptrons (MLP). They are the most employed and studied neural model nowadays.

More information on Artificial Neural Networks can be obtained, for instance, in many sources, such as [Haykin 1999] for a rigorous approach and [Fausett 1994] for easy understanding.

2.3. Tutoring Systems

The use of computers in the Education has begun in the fifties with the creation of tutoring systems [Richmond 1967] in the areas of Computer-based Training (CBT) and Computer Assisted Instruction (CAI). Such programs are considered simple "electronic books." To provide personalized tuition, Intelligent Tutoring Systems (ITS) were coined

in [Sleeman & Brown 1982]. Many successes have been collected by using ITS because they act on students' performance and motivation [Shute et al 1989].

In order to contextualize the present proposal, using intelligent systems based on artificial neural networks, it is important to present the principal structures usually employed. An initial test states the beginning of the lesson and, in the end, a summary is presented for revision of the concepts, followed by test or other activity to measure the acquired knowledge.

In classical tutorial, users access the content in basic, medium and advanced levels progressively. In the tutorial focused in activities, another activity with some information or additional motivations precedes the accomplishment of the goal activity. In the tutorial customized by the apprentice, between the introduction and the summary, there are cycles of pages of options (navigation) and content pages. The page of options presents a list of alternatives for the apprentice or a test in the sense of defining the next step. In the progress by knowledge tutorial, the apprentice can omit con-tents dominated already, being submitted to tests of progressive difficulty to determine the entrance point in the sequence of contents. In exploratory tutorial, the initial page of exploration has access links to documents, databases or other information sources. In lesson generating tutorial, the result of the test defines the personalized sequence of topics to be exposed the apprentice.

Other recent structure proposes connectionist tutoring systems [Martins and Carvalho 2004] [Martins et al 2004]. In this approach, contents are partitioned in several topics (contexts). Each context is divided in five levels: facilitated, medium, advanced, frequent answered questions and examples.

2.4. Basic Hybrid Intelligent Tutoring System

The use of Artificial Neural Networks is not wide spread as far as Intelligent Tutoring Systems are concerned [Prentzas and Hatzilygeroudis 2002]. On the other hand, this work is based on the model described in [Martins et al 2004]. This specific ITS searches to improve the student's performance by considering learning styles in the generation of the navigation patterns. A navigation pattern establishes the distributions of probabilities of visitations of the five levels in each context (See Figure 2).

Besides considering individual preferences and knowledge, the system takes into account your level of technological ability (to work with the technology used to implement the interface with the user). In this case, computers are used as interface. The system tutor exhibits, after each content presentation of every level, an objective test with alternatives of different correctness degrees. In other words, there is also a good option besides the best one.

In the structure, it is employed only one net for the whole tutor, a generic one that would be useful for every kind of lesson. The decision of the proposed ITS is based on the navigation pattern generated by ANN and on the apprentice's local acts (current level and his performance in the corresponding test).
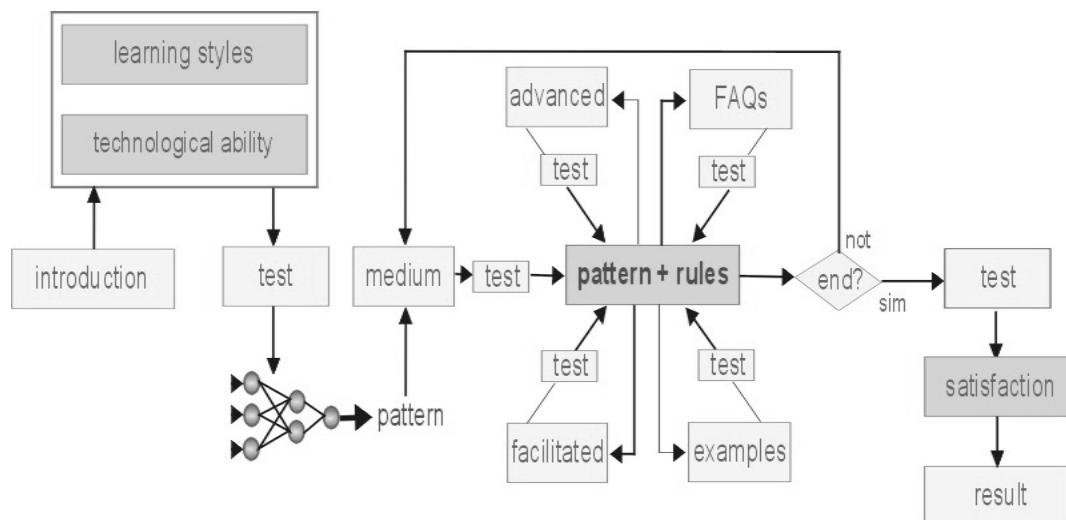
Figure 2. Architecture of the Hybrid Intelligent Tutoring System [Martins et al 2004].

To complement the generic decision of the intelligent navigation and to exercise more sensitive control to the apprentice's local acting, a group of symbolic rules is added to the system. The definition of the symbolic rules is made by experts in teaching. The rules treat existent situations in agreement with the structure of the tutor (composed of context levels and tests), and state the chances of available levels (or next context) faced to the acting in the level just accessed.

To define the next step in the tutor, the intelligent system has the student's profile, the symbolic rules, the visited level and the answer at the last exercise. In agreement with the level and the answer at the exercise, the system retrieves, from the group of symbolic rules, the rule of probabilistic indications for the specific local (current) situation.

The data collected in a free navigation (in the same structure without ANN) were used to train the net. The efficiency of this system is measured based on the acting of the guided navigation. Efficiency (E) it is directly related with of the student's productivity (P) and it is inversely proportional to the used resources (R) (visited levels, number of neural nets, session duration, etc) [Chiavenato 1998].

Another aspect of the system is the capture of apprentice's satisfaction during the interaction with the tutoring system. The satisfaction is defined by apprentice's impressions at the execution of the tutor such as: global evaluation, feeling and tiredness.

By employing inferential statistical tests, reported results shown that the intelligent guided navigation is actually superior (significant at 5%) to the free and random navigations.

The inclusion of conceptual maps is undertaken in this system. Figure 3 summarizes the main aspects of this basic system.

3. Proposed System

This work uses the architecture of the Hybrid ITS developed in [Martins et al 2004]. However, we have included a new element: the interactive conceptual map. It is

believed that the inclusion of conceptual maps after the intermediary level can contribute to better results, that is, students will get better marks and even maintain the learned information longer. Such facts are expected because the manipulation of concepts reinforces and stimulates cognitive capacities (mainly verbal ones) of the apprentices and creates, therefore, a favorable environment for meaningful learning. The architecture of the proposed system is presented in Figure 3 (see below).
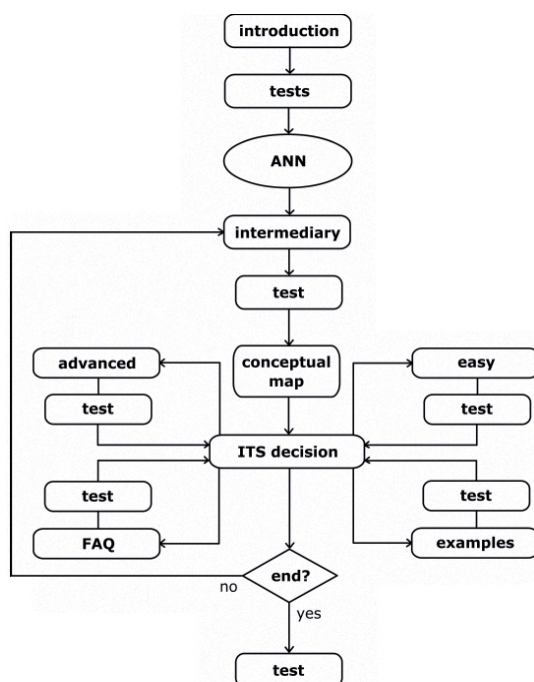
Figure 3. Dynamics of the Proposed System.

The module of conceptual map presentation, as shown in Figure 4, is composed of three main parts:

- The Concept Menu (CM), part 1, stores concepts of a specific context. These concepts are related to the intermediary level.
- The Work Area (WA), part 2, is used to compose the conceptual map. Several rectangles serve as inclusion locus to concepts. The distribution of rectangles is previously defined and it is not always hierarchical.
- The Status Area (SA), part 3, where the user is informed of how his work is evolving, that is, some feedbacks like "Right Answer" and "Wrong Answer", besides the possibility to show the right answer.

As shown in Figure 4, at this research stage, the proposed system maintains fixed conceptual maps structures. In fact, this is not even common to conceptual maps studies [Novak 1998], but it is feasible stage and introduces some user interactivity to the basic version, that is our main concern.
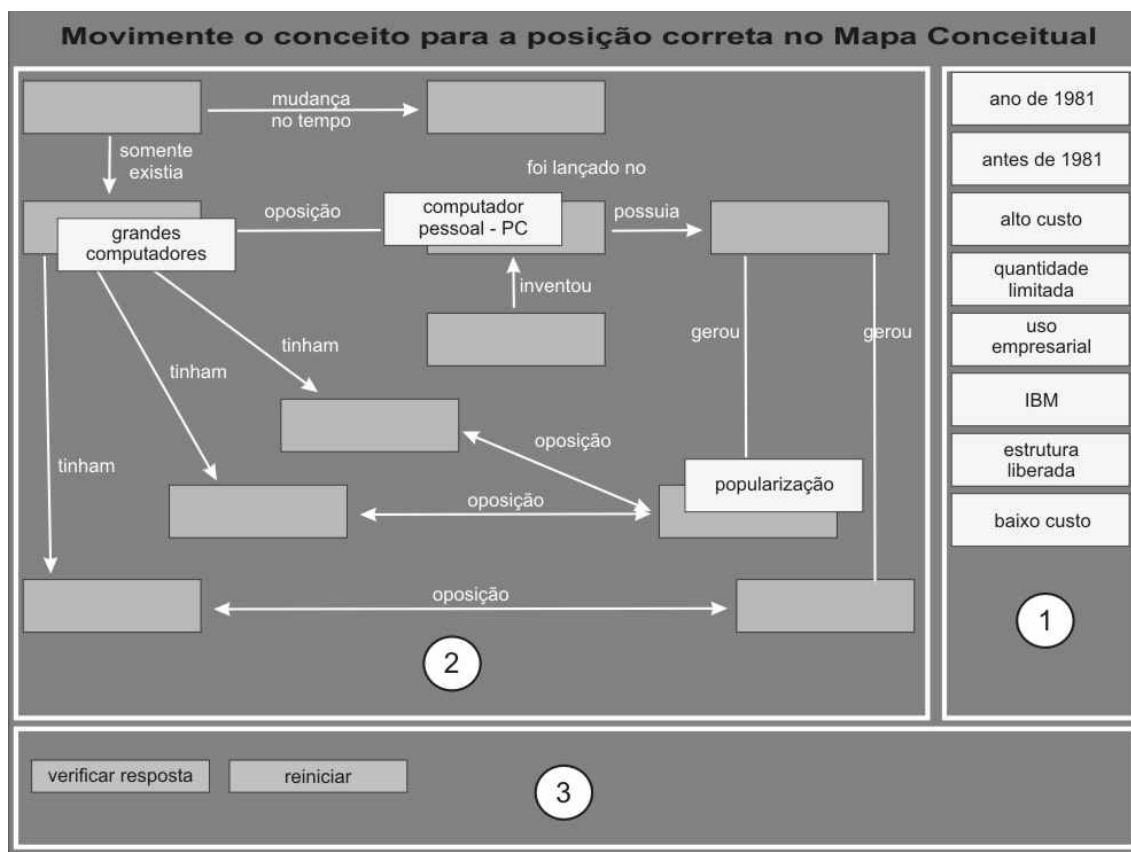
Figure 4. Screenshot of Proposed System

4. Results

The composition of the (neural) training set has lead to the implementation of a tutoring system for the data collection, called Free Tutor, and an Intelligent Tutor. Undergraduate students in Administration course have composed our samples. The contents have covered a lesson in a course of "Introduction to Informatics". After the training of the neural networks, a new data collection was made to record the Intelligent Tutor with and without conceptual maps for comparative studies, called basic and improved intelligent navigations respectively.

At the end of the data collection, 234 navigations were considered valid. Among them, 148 free navigations, 31 basic intelligent navigations, and 55 improved intelligent navigations where conceptual maps were included. Table 1 indicates statistical descriptive measures of the observed initial and final marks, and the normalized gain of each student in each condition: free, basic intelligent and proposed system.

In descriptive terms, the inclusion of conceptual maps has improved the average final mark and the normalized gain. The free condition, where the user has full control of his navigation, is the poorest approach. It should be noted that only navigations with normalized gain above 50% were selected to the neural network training set.

Table 1. Descriptive statistics of collected data

	Initial Mark			Final Mark		
	Free	**basic**	**proposed**	**free**	**basic**	**proposed**
Average	4,56	3,72	4,51	6,87	7,29	7,93
Std Error	0,15	0,42	0,32	0,14	0,33	0,19
Median	4,40	3,60	4,80	6,80	7,47	8,27
Mode	3,60	2,00	1,33	8,80	7,47	8,80
Std Deviation	1,78	2,35	2,41	1,66	1,81	1,43
Kurtosis	-0,74	-0,79	-1,05	-0,06	0,76	0,53
Skewness	0,18	0,17	-0,43	-0,34	-0,78	-0,87
Range	8,13	8,93	8,27	8,53	7,20	5,87
Minimum	0,67	0,00	0,00	1,47	2,80	4,13
Maximum	8,80	8,93	8,27	10,00	10,0	10,0
# cases	148	31	55	148	31	55

In order to do the inferential analysis of the collected data, the t-test was selected and the level of significance was chosen to be 5%. On the initial marks, these tests have shown significant differences between free and intelligent navigations only. Moreover, this difference favors the free condition and states that it has begun with a better student sample (see Table 2). Even though, the free condition was clearly surpassed by the other two conditions.

Table 2. Initial mark inferential statistical analysis of free X basic hybrid ITS conditions

Conditions	Basic H ITS	Free
Average	3,72	4,56
Variance	5,50	3,17
# cases	31	148
T	2,26	
P (T <= t)	0,02	
t critic bicaudal	1,97	

On the final marks, the use of the t-test has indicated significant differences when the system with and without conceptual maps were compared. The comparison between the proposed system and the free condition has also revealed significant differences (see Table 3). Not surprisingly, no significant difference has been shown between the basic intelligent and the free conditions. Perhaps, it is due to the fact that the basic intelligent condition has started with an inferior student sample. If one uses a normalized gain measure to compute how much a student has improved compared to his maximum improvement, this hypothesis can be verified as acceptable.

Table 3. Final mark inferential statistical analysis of free X basic hybrid ITS conditions

Conditions	Proposed System	Basic H ITS
Average	**7,92**	**7,28**
Variance	**2,05**	**3,27**
# cases	**55**	**31**
T	**1,80**	
P (T <= t)	**0,03**	
t critic bicaudal	**1,66**	

In terms of normalized gain, that is, the percentual gain (see Equation 1) over the initial mark relative to the maximum mark that would be possible (in this case, 10), there was no significant difference when the basic hybrid ITS is compared to the proposed system. Both, however, are better than free navigation according to t test. Averages in free, basic hybrid ITS and proposed system were, respectively, 39.59%, 57.76% and 60.89%.

$$\text{Normalized Gain} = (\text{Final\_Mark} - \text{Initial\_Mark}) / (10 - \text{Initial\_Mark}) \qquad (1)$$

Finally, it should be said that some reports of tiredness were received from the users of the proposed system. On the other hand, this feature has not prevented the improved hybrid ITS of showing a more effective experience of knowledge acquisition and retention overall.

5. Conclusions

In this study, an environment for conceptual maps presentation and interaction has been introduced in a hybrid ITS and empirical validation has indicated its promising features. In this new environment, it is possible to manipulate concepts and the building of conceptual maps. The comparison between the proposed system and the basic ITS has indicated the effectiveness of the inclusion of conceptual maps.

Both ITS have shown superior to free navigation when normalized gain and Inferencial statistics are employed. In terms of final marks, the proposed system has overcome the basic hybrid ITS with 5% significance despite the fact that, in terms of initial marks, they have not presented significant differences. Free navigation was the poorest approach based on empirical findings.

In future studies, it should be considered the possibility of human analysis of students' answers in each conceptual map. The proposed system records the number of wrong and right decisions. Therefore, teachers could identify missing points in the organization of each subject, which maps were the most difficult ones and if contents is presented accordingly. The student freedom to compose conceptual maps is also another important variable to study in the future.

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