An Intelligent Tutoring System Based on Self-Organizing Maps – Design, Implementation and Evaluation

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Abstract. This work presents the design, implementation and evaluation of an Intelligent Tutorial System based on Self-Organizing Maps (neural networks), which is able to adapt, react, and offer customized and dynamic tuition. The implementation was realized in web environment (and technology). On the instructional design, the content, source of knowledge to be learned, has been modeled in an original way and is adequate to neural control. At the evaluation, two user groups have been compared. The first one (the control group) moves freely in the content, while the other group (the experimental group) is guided by the decision of neural networks previously trained from the most successful free interactions. Therefore, the control group serves not only as reference but also as source of good examples. Statistical techniques were employed to analyze the significance of sample differences between the two groups. Results from the interaction time have shown significant differences in favor of the guided tutor. All users guided by the intelligent control have performed as well as the best ones which had freedom to navigate through the content.

1 Introduction

Since 1950, the computer has been employed in Education as an auxiliary tool towards successful learning [1] with Computer-Assisted Instruction (CAI). The inclusion of (symbolic) intelligent techniques has introduced the Intelligent Computer-Assisted Instruction (ICAI) or Intelligent Tutoring Systems (ITS). The adaptation to the personal user features is one of the main characteristics of this new paradigm [2].

Despite the evolution of ICAI systems, the tutoring methods are basically defined by the expert conceptual knowledge and by the user learning behavior during the

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tutoring process. Besides, the development of such systems is limited to the field of symbolic Artificial Intelligence (AI).

In this article, the use of the widest spread subsymbolic model, artificial neural networks, is proposed with an original methodology of content engineering (instructional design). Additionally, some experiments are reported in order to compare the proposed system with another system where content navigation is decided by the user free-will. These navigations are evaluated and the best ones are extracted to build the neural training set. Alencar [3] has introduced this idea with no empirical evidence. He has shown that multilayer perceptrons (MLP) networks [6] could find important patterns for the development of dynamic lesson generation (automatic guided content navigations). Our work employs a different neural model, self organizing maps (SOM), which adaptively builds topological ordered maps with reduction of dimensionality.

The main difference between this proposal and traditional ICAI systems is related to the need of expert knowledge. No expert knowledge is required in our work.

1.1 Self-Organizing Maps

Self-organizing maps were introduced by Teuvo Kohonen [4]. They have biological plausibility since similar maps have been found in the brain. After the training has taken place, neurons with similar functions are situated at the same region. The distance between neurons shows the difference of their responses. Similar stimuli are recognized (lead to highest responses) by the same set of neurons which are at the same region of the topological ordered map.

Self-organizing maps are composed basically by one layer (if it is not considered the input layer, where each input is perceived by one neuron), see Fig. 1. Training implements competitive learning: neurons compete to respond to specific input patterns, the ones that are more similar with their own prototypes (which are realized by the synaptic weights). Neurons are locally connected by a soft scheme. Not only is the most excited neuron involved at the adaptation process but also the ones in his neighborhood. Therefore, not just one neuron learns to respond more specifically but the entire region nearby.

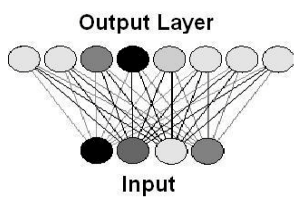

Fig. 1. Example of a self-organizing map

The specification of the winner neuron is performed typically by using the Euclidian distance between the neuron prototype and the current input pattern [5]. Fig. 2 shows and example of topological map built to order a set of colors (represented by red, green and blue components). At the end of the training, neurons at the same region are focused at similar colors. Two distant neurons respond better to very different colors.

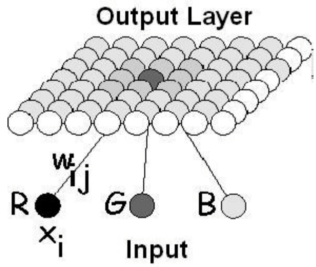

Fig. 2. Weights associated to each input

The initialization of neurons prototypes are done at random. Sometimes, this tactic is abandoned if the examples are not very spread in the input space (for instance, the colors are all redish). An alternative is the use of randomly chosen samples from the training set. SOM training is conducted in two phases. The first one is characterized by global ordering and fast decreasing of neighborhood while the second one does local and minor adjustments [8].

The definition of the winner neuron in Self-Organizing Maps could be done by using several metrics. The commonest procedure is the identification of the neuron that has the smallest Euclidian distance in relation to the presented input [4]. This distance can be calculated as shown below.

$$D_{i,j} = \sum_{i=1}^{n} \| x_i - w_{ji} \| \tag{1}$$

where:

$D_{i,j}$ is the distance between the j-th neuron and n-dimensional input pattern

x_i is the i-th dimension of the input pattern

w_{ji} is the conexion weight of the neuron related to the i-th dimension of the input pattern.

2 Proposed System

The idea of creating an intelligent tutoring system, capable of dynamic lesson generation, based on neural networks has been originated from the interest of developing a system able to decide without expert advice. Such constraint is commonly found in the literature [7].

In the proposed system, neural networks are responsible for the decision making. They are trained to imitate the best content navigations that have been encountered when users have been guided by their free-will. Notice that the control group is also the source of knowledge needed to train the neural networks employed in the experimental group. Our target is to produce faster content navigation with performance similar to the best occurrences in free navigation.

The first phase is the data collection originated by free navigation. Fig. 3 shows its dynamics and, in particular, the content engineering. Lessons are organized in sequences of topics. Each topic defines a context. Each context is expressed in five levels: intermediary, easy, advanced, examples and faq (frequent answered questions). The last two levels are considered auxiliary of the others. The intermediary level is the entry point of every context. The advanced level includes extra information in order to keep the interest of advanced students. The easy level, on the other hand, simplifies the intermediary context in an attempt to reach the student comprehension. The example level is intended to students that perceive things by concrete situations. The faq level tries to anticipate questions commonly found in the process of learning that specific content.

After the contact with each level (in all contexts), learners face a multiple-choice exercise. Before the lesson starts, there is a need to introduce aspects of the environment to the learner and to implement an initial evaluation. After the lesson, there is a final test in order to measure the resulting retention of information (that will serve as an estimate of the learning efficiency).

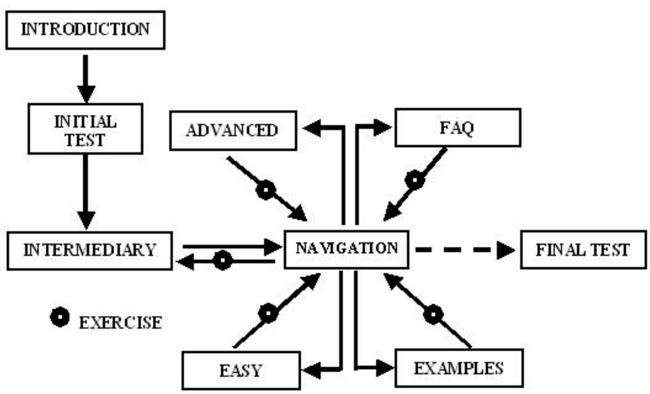

Fig. 3. Structure of navigation

At the second phase, the navigation is guided by neural networks specifically trained to imitate the decisions of the best users at each point. Therefore, there is one distinct SOM for each level of every context. At the end of the interaction with the "theoretical" content and the following exercise, a SOM is fed with the current state in order to decide to where the user should be sent (a different level of the same context or the intermediary level of the next context).

2.1 Implementation

Despite the typical use of two-dimensional SOM, we have opted in favor of unidimensional SOM disposed at a ring topology (with 10 neurons each). The training of each SOM was completed after 5,400 cycles. Each SOM was evaluated for global ordering and accuracy. To force SOMs to decide on destinations within the tutor, there is a need to label each neuron. This labeling was carried out by a simple ranking rule where the neuron responds the destiny to which it was more similar (in the sense of average Euclidian distance) at the training set. If a neuron has been more responsive to situations where the next destiny is the next context so this is its label, its decision when it is the most excited neuron of the map (refer to [9] for details).

2.2 Experiments

Students (randomly chosen) from the first year of Computer Engineering and Information Systems from the State University of Goiás were taken to test our hypotheses. Some instruction was given to the students to explain how the system works. Individual sessions were kept below one hour. The experimental design has involved, therefore, two independent samples. Initial and final tests were composed by 11 questions each. The level of correctness and the time latency were recorded throughout the student session.

Twenty two students have been submitted to the free navigation. One of them was discarded because he has shown no improvement (by the comparison of final and initial evaluations).

The subject of the tutor was "First Concepts in Informatics" and was structured in 11 contexts (with 5 levels each). As a consequence, 55 SOM networks were trained. The visits to these contexts and exercises have produced 1,418 records.

2.3 Results

With respect to session duration, a relevant aspect in every learning process (particularly in web training), we have performed the comparison between control and experimental groups by taking out initial and final tests. Fig. 4 shows average session duration at each group. By applying the t-test, we have confirmed the hypothesis of significant less time spent by the experimental group (an approximately 10-minute difference has occurred in average).

The application of the t-test has resulted in an observed t of 2.65. By using level of significance of 5% and degree of freedom (df) of 39, the critical t is 1.68. Therefore, the observed t statistic is within the critical zone and the null hypothesis (that states no significant differences) should be rejected in favor of the experimental hypothesis.

With respect to the improvements shown by means of the initial and final tests, we have compared the control and experimental groups by employing the t-test again. By doing so, we have tried to assess the learning efficiency of both methods.

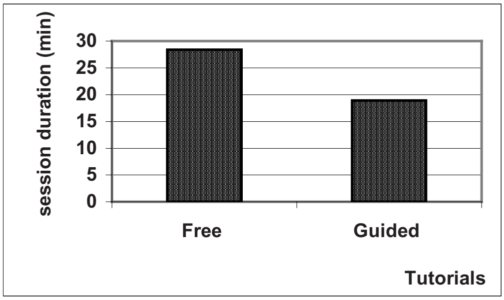

Fig. 4. Average section duration

Fig. 5 shows the average of corrected answers in both tests. One can see that the control group has produced slightly better averages. In fact, these differences are not significant when inferential statistics are employed. The observed value of the t was 1.55. As before, the critical t is 1.68 and there are 39 degrees of freedom when a level of significance of 5% is used. In this situation, the observed value is outside the critical zone and the null hypothesis should not be rejected based on this empirical evidence. Therefore, we should not reject the hypothesis that observed differences have occurred by chance (and/or sample error). Furthermore, one should notice the occurrence of relevant improvement in both groups. In the end, students have more than doubled their corrected answers. We should remind that each test is composed of 11 questions (one question for each one of the contexts).

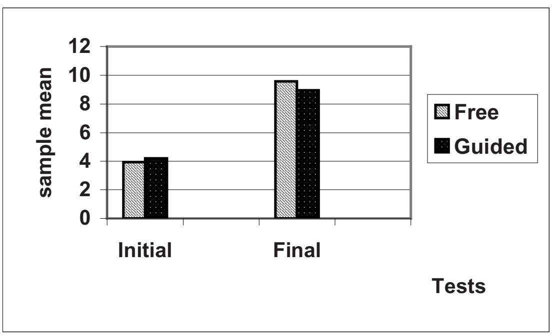

Fig. 5. Average of corrected answers in tests

3 Conclusion

This article has formalized the proposal of an intelligent tutoring system based on self-organizing maps (also known as Kohonen maps) without any use of expert knowledge. Additionally, we have implemented this proposal in web technology and tested it with two groups in order to contrast free and intelligent navigation. The control (free navigation) group is also the source of examples for SOM training.

The content is organized in a sequence of contexts. Each context is expressed in 5 levels: intermediary, easy, advanced, examples and frequent answered questions. The subject of the implemented tutor was "First Concepts in Informatics" and was structured in 11 contexts. This structure is modular and easily applied to other subjects which is an important feature of the proposed system.

Results from experimental work have shown significant differences on session duration with no loss of learning. This work contributes in the sense of presenting a new model for the creation of intelligent tutoring systems. We are not claiming its superiority but its right for consideration in specific situations or in the design of hybrid systems.

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