A Confidence Agent: Toward More Effective Intelligent Distance Learning Environments

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ABSTRACT

In this paper, we propose a multi-agent approach to building more Cooperative Intelligent Distance Learning Environments (CIDLE). We define a *Confidence Agent* in Intelligent Tutoring System (ITS) in such a way that an ITS would improve the quality and efficiency of its teaching. To achieve this goal, we propose a *Confidence Intelligent Tutoring System* (CITS) to manage negotiations within a community of on-line learners to improve CIDLE interactions among the participants. The proposed system can extract knowledge about domain knowledge and about learners behavior during a learning discussion. Therefore, it infers the behavior of learners, and adapts presentation of subject mater in order to improve their success rate in answering questions and boost their self-confidence during learning session. In addition, we discuss architectural problems of the CITS and their solutions..

Keywords: Cooperative Intelligent Tutoring System, Distance Learning, Multi-agent, Confidence agent, KQML.

1. INTRODUCTION

Web-based tutoring systems have contributed to improve intelligent distance learning. Using those systems, learners usually depend on long-distance, asynchronous communication (e-mail, newsgroups) or synchronous communication (web-conferences, chat-rooms) to find solutions for problems. But most of those systems cannot adjust learning materials to meet individual needs [4]. Although some tutoring systems have correct information and higher levels of competence than those of the learners, difficulties persist: a learner might lack the motivation to complete a learning session [12], for instance**,** or dislike the learning style. The main reason is that learners have varying levels of knowledge, learning styles, and needs. These tutoring systems apply the same approach to all learners and cannot deal with them as individuals, which undermines confidence in the systems.

The origin of the above problems resides in the fact that the existing CIDLE that rely on the Web to disseminate knowledge have some very serious weaknesses. They neither support a high quality communication with each learner, nor do they adapt the information they provide to meet the learner's individual needs. Our research will focus on how to build more effective CIDLE.

According to [7], and [1], our hypothesis is that if we strengthen confidence between the learner and the proposed system, this would increase learning quality. Our approach is to build an intelligent cooperative system that takes into consideration not only varying levels of knowledge but also varying styles of learning and learner's behavior during the previous learning session. This system must still be adaptive, learnable and dynamic. It can find out a missing knowledge during a learning session between two learners and then provide it for both of them. It can provide the learners with different fragments such as new definition, extra information, images, applet, and so on. Consequently, these properties can satisfy our goal to increase confidence in the system.

A major part of this research tries to presents answers to the following challenges: What type of knowledge is useful for adaptation? How can we elicit this type of knowledge from learners? How can categorize the knowledge as a function of the various adaptation needs? How can the suggested system find learners with similar interests and learning needs? How can the suggested system improve and facilitate a conversation between learners?

This paper is organized as follows. In section 2, we briefly describe related works that support adaptation task. In section 3, we define "confidence agent" so that an ITS is more engaging. In section 4, we describe in detail an architecture based on the confidence agent (CITS). In section 5, we show how CITS feeds its knowledge base. In section 6, I explain the language of communication among agents and present the CITS current version. Finally, in section 7, I discuss pending problems and suggest future projects.

2. RELATED WORKS

Before discussing the proposed architecture, we find it necessary to discuss related works to our proposed system.

ELM-ART [3] is a web-based ITS designed to teach an introductory LISP course. It supports learners navigating the course with visual cues (icons, fonts, colors) that show the type and the educational state of each link. ELM-ART is adaptive when it comes to navigation but not when it comes to presentation. It lets them follow only existing links. It has only text materials, moreover, not multimedia ones. ATS [16] is a web-based ITS designed to teach an introductory statistics course. Although the ATS framework relies on the psychology of learning to adapt presentation and navigation, it does not deal with learners individually. Both systems lack knowledge and acquisition and multimedia materials. Moreover, they do not rely on any multi-agent technique.

Our multi-agent system provides a dynamic adaptation not only of domain knowledge but also of the behavior of individual learners during learning session.

The next section describes definition and the main characteristics of a confidence agent in intelligent tutoring systems.

3. DEFINITION FOR CONFIDENCE AGENTS IN INTELLIGENT TUTORING SYSTEMS.

The idea of a "confidence agent to learn and teach" is becoming more common in the ITS community. Our proposed architecture aims to give a confidence to learners based on the following definition of a *confidence agent:*

Definition: *an agent which can guarantee confidence conditions between learners during a learning discussion through a learning distance is called a confidence agent.*

Taking into account the National Board for Professional Teaching Standards [17], and learner models [8, 11], I propose that the following goals be achieved by a confidence agent. A confidence agent should be:

Reliable:

A confidence agent is devoted to both learners and learning. It knows the behavioral differences that distinguish one from another and takes these into account. It changes their exercises according to levels of knowledge, ability, and skill. It takes into consideration the impact of culture on their behavior.

Knowledgeable:

A confidence agent knows the subject matter to be taught and how to teach it. It knows how to convey subject matter to students. A confidence agent understands where difficulties are likely to arise and how to modify the procedure according to knowledge levels, learning styles, and behaviors of the learners. It offers many paths to every subject, which allows it to adapt its approach to each learner.

Responsible:

A confidence agent is responsible for managing and monitoring student learning. It has many methods for measuring learner progress and can increase the level of knowledge. It has social roles, too, engaging learner groups with the same goals.

Learnable:

A confidence agent thinks systematically about its practice and learns from experience. It can learn a new technique from its learners and adapt itself in experimental and problem-solving ways. It updates its knowledge. It is willing to strengthen its teaching by taking into account the opinions of learners about its practice, repertoire, and knowledge.

Contributing:

A confidence agent contributes to other external tutoring agents to update instructional policy, curriculum development, and new techniques in teaching. It can contribute to related knowledge sites on the Internet to update its knowledge.

In this paper, we try to satisfy some of these requirements of a confidence ITS. The following section explores architecture and ways of attaining a reliable, knowledgeable, responsible, learnable, and contributing ITS.

4. THE CITS ARCHITECTURE

Figure1 represents the proposed multi-agent CITS architecture. The proposed architecture defines five types of agent: the cognitive agent, the confidence agent, the behavior agent, the guide agent, and the information agent. Agents work individually or together to give a solution for one of the above challenges. The mains roles and implications of the different agents are the following: the *cognitive agent* aims to catch domain knowledge to be useful for a learner, and the *confidence agent* is work as an adaptive agent to provide the facilities for reconciling the other four agents to various types of knowledge from the learners and intended for the other agents, the *behavior agent* observes learner's behavior during interaction with the system to update the learner model in the light of evidence gathered to

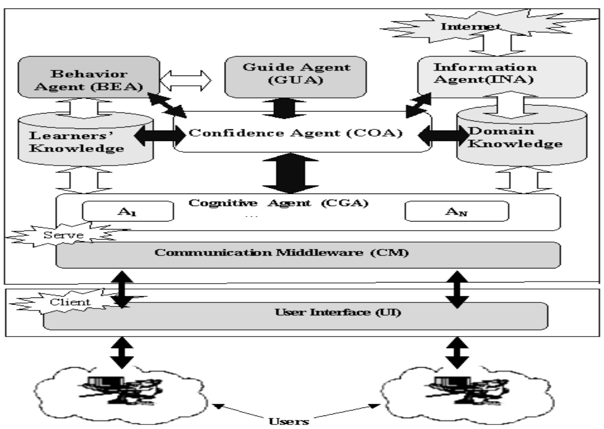

Figure 1. The CITS Architecture.

use in adaptation, the *guide agent* aims to find learners with similar interests and introduce them to each other, the *information agent* manages and prepares produce individualized course, and to establish the conditions of a successful conversation between learners. Before we explain the characteristics of each agent, we need to present how the domain knowledge represented in our system.

4.1 Knowledge representation

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 [10]. The knowledge base of the proposed system recommends two types of learning fragments: *i*) Material of domain knowledge text, examples, and exercises. *ii*) Material consisting of image, video, audio, and applet files. In this sense, we constructed the domain knowledge in the three layers of hierarchy architecture, as shown in Figure 2, with each layer providing a different type of knowledge. The architecture is based on the notion of *knowledge targets* that learners willingly adopt, in an attempt to provide a way for learners to control the environment in which they learn. The knowledge target **T (c, t, i, a, em, er, v, au)** is a vector consisted of 8 components: the concept requested to study **(c)**, text unit **(t)**, image unit **(i)**, applet unit **(a)**, example unit **(em)**, exercises unit **(er)**, video unit **(v)**, and audio unit **(au)**. The characteristics of each agent are as follows:

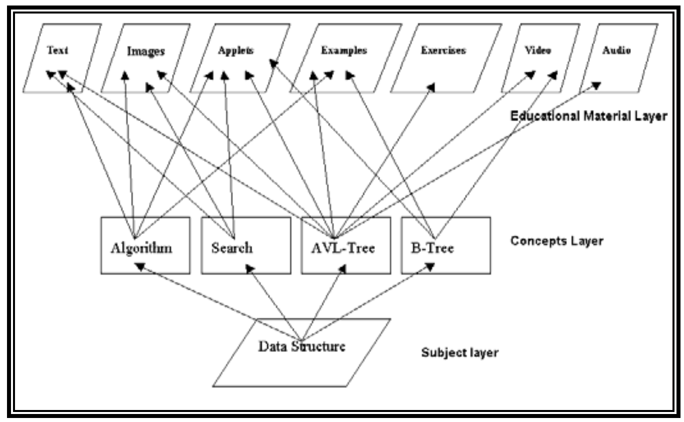

Figure 2 Domain Knowledge Representation

4.2 The Cognitive Agent

The Cognitive Agent (**CGA**) helps CITS to be more reliable. The CGA, close to learners, is in charge of acquiring knowledge about them - such as their learning profiles, knowledge level, and learning style. The CGA create a learner model for each learner. The learner model represents the learner's learning style and knowledge levels.

The first time learners use the system; the CGA encourages them to fill out short questionnaires asking for user name, password, sex, age, and interests (expertise, projects). This basic information is stored in the database. Afterwards, the proposed system fellows two ways to evaluate the learning style of each student: a short term method, and a long term method. In the short term method, the CGA based on the experiment results ID3 Decision Tree Induction Algorithm determines the learning style of the learners, more details in [18]. The CGA lets the learner to choose the colors they like best, second best, third, and so on, until eight have been chosen. This color sequence is then applied by ID3 algorithm to identify his learning style. The long term method is a task of the behavior Agent (more detail in the Behavior Agent).

Following Anderson [2], The CGA distinguishes some types of learning style: visual; visual & auditory; visual & kinesthetic, and visual & auditory & kinesthetic. Visual learners must see the material to learn most effectively. Auditory ones learn best by hearing it. And kinesthetic ones learn best by doing something. The choice of a learning style takes success into consideration. In other words, the style that works best is rated as relevant one.

Learners are submitted to tests to evaluate their understanding. The CGA takes into account the number of questions and exercises tested, the scores obtained, the number of attempts required before giving correct answers, and the frequency of misconceptions. Following [10], we classify the knowledge level into categories such as {EI, I, RI, RS, AS, S} = {Extremely Insufficient, Insufficient, Rather Insufficient, Rather Sufficient, Almost Sufficient, Sufficient}.

4.3 The Behavior Agent

The behavior agent (**BEA**) is in charge of confirming the learners' learning styles [18] which were initially received from a questionnaire submitted by the CGA. The BEA aims to confirm of infirm and complete the information about the learning style. We suggest a long term method to verify whether the learner's style determined by CGA is correct or must be changed. The long term method is responsible of studying learner's behavior during each the learning session: What fragment of text has he read? How many images has he requested? How many video has he watched? How many audio has he listen? And so on.

The answer of all these questions is included in the knowledge target vector **T (c, t, i, a, em, er, v, au)**. The BEA based on a machine learning technique (ID3 Decision Tree Induction Algorithm) analyzes all these vectors related to each learner to predict the learner's behavior and fragment module in order to determine the next knowledge target according to his educational needs. The fragment module is in charge of selecting the most appropriate basic course fragments to be presented to the learner based on the performance of the learner on previous course units, and the learner models.

4.4 The Guide Agent

The guide agent (**GUA**) selects and classifies information which can be useful for the learner. It uses a hierarchy to classify relations between the subject matter and the learner's knowledge level. Consider that learner L_3 asks a question about the AVL tree in Data Structure subject. The problem is how the GUA selects another learner with an adequate knowledge on the AVL tree to communicate with learner L_3. As shown in Figure 3, the first level identifies the subject's name.

The second identifies its sections/aspects. The third ranks level of understanding according to the following scheme: {EI, I, RI, RS, AS, S}. The last level consists of all learners. Each section/aspect in the second level is associated with all ranks in the third. The ranks of all students are associated with those of corresponding learners at the last level. We will return now to the example. The GUA goes to the AVL tree section at the second level and then checks the associated learner with the rank S. If there is at least one learner, say L_1, he or she will be selected. If not, it will select rank AS and so on. The GUA agent takes into account the new learner's knowledge level. It should be better than that of learner L_3.

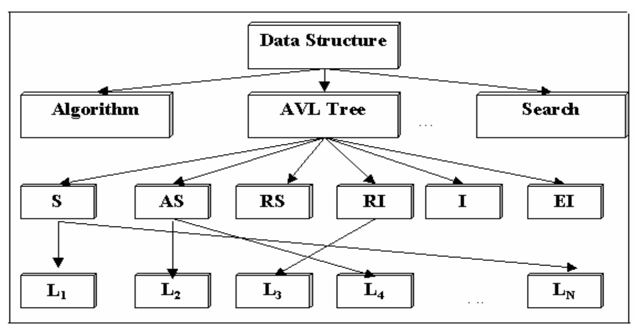

Fig. 3. Hierarchy Classification for the Subject and the Learners

4.5 The Information Agent

The information agent (**INA**) deals with domain knowledge and information obtained from the Internet. During a learning session, the INA can search the Internet for extra information required by a learner. Some learners prefer to deal with abstract information; others prefer to watch videos. And still others prefer to hear audio tapes or access applets.

The INA creates an assessment component. The assessment component records the usage of the concept, the text fragments, and the performance of learners on the exercises and examples, and the comments from the learners. The answer of all these questions is included in the knowledge target vector **T (c, t, i, a, em, er, v, au)**. One mechanism for achieving this form is reinforcement learning [17]. The INA based on the reinforcement learning method analyzes all these vectors related to the concept (**c**) to predict the best knowledge target according to this concept. This knowledge target is utilized to adapt the material of subject matter to the learner.

4.6 The Confidence Agent

The goal of the confidence agent (**COA**) is to strengthen confidence between the proposed system and learners by which learning quality would be increased. We think that if the proposed system can present courseware in a good way related to the learners needs, this way creates a confidence between the proposed system and the learners and increases learning quality.

In the CITS, communications do not occur directly between learners but rather through the confidence agent (**COA**). The COA works as a central agent for all agents in the proposed system. It is in charge of two tasks: one is to adapt material course according to learners' individual needs, and the other is to measure the performance of this adaptively. The whole system serves the COA which receives all relevant information about interests, learning styles, and the learning materials coming from others agents. This information allows the COA to analyze: *i*) the specific behavior of each learner, *ii)* discussions among learners, and *iii*) specific and complementary types of knowledge coming from the Internet.

For example, consider that *a goal* of a group of learners is to study a concept in Data Structure, say AVL-Tree. Consequently, the CGA, and BEA, and INA provide The COA with a learner model, a fragment module and a knowledge target vector. According to these cueing, the COA produces a *path* which combines the extracted knowledge and the content of the course to produce a coherent educational courseware component. This path can reformulate question and its response according to learners' behavior during learning session.

The second aim of the COA is to measure the performance of adaptivity. This measurement is based on observations of past performance of paths and on inferred reasons for that performance being what it was. This measurement assists the COA to make good decisions during execution. The availability of different paths for a goal gives flexibility to the choice of a best path for that goal. The meaning of the best path is related to: the likelihood that each path will lead to success. The successful execution of a path only guarantees the success of the goal if the learners agree that this path gives them a good way for understanding the concept and the success condition is satisfied. The performance of the paths is measured. Paths which do not succeed are to be avoided. One mechanism which will be used for determining the best path is reinforcement learning [17].

5. ACQUISITION THROUGH DISCUSSION

More knowledge can be obtained through the cooperative learning sessions. Basically, the CITS allows each learner to build more knowledge on a given subject after discussions between the learners. The goals are to acquire new materials related to the subject from learners themselves and to modify the presented material's weight according to the user's recommendation. For example, if the COA has many answers for one request, the COA offers them to learners and asks them to recommend what they prefer.

After the COA has interacted with enough learners, it can establish good relations between requests and responses. At the next learning session, the COA can recommend the highest weight response to a learner who makes the same request. In the following section, we show how the various agents in CITS can communicate.

In the following section, we show how the various agents in CITS communicate among themselves and the CITS current version.

6. AGENT COMMUNICATION LANGUAGE AND IMPLEMENTATION

Indeed, we need to design an agent communication language. There are two ways of doing this [9]: a procedural way and a declarative one. In the procedural way, communication is based on executable content using programming languages such as Java or Tcl. In the declarative way, it is based on declarative statements, such as definitions, assumptions, and so on. Currently, there is a declarative method called Knowledge Query and Manipulation Language (KQML), which is most popular because of its suitability for communication among agents.

We have used a subset of KQML to define a language and protocol for exchanging information and knowledge. It is both a message format and a message-handling protocol to support run-time knowledge sharing among agents [5]. For example, Figure 5. shows the format of a KQML message and its response in connection with the question in section 4.4.

```
(Ask
   :sender    COA
   :receiver  GUD
   :content   "Learner(AVL-Tree, [?S])"
   :language  PROLOG
   :ontology  Data Structure
 )
```

Figure 5 KQML example form The COA to the GUA

```
(Tell
   :sender    GUD
   :receiver  COA
   :content   "L1"
   :language  PROLOG
   :ontology  Data Structure
 )
```

Figure 6 KQML example form The GUD to the COA

A message in Figure 5 represents a question about the sufficient learner, someone who know about AVL-Tree section/aspect. The KQML performative is Ask, the ontology assumed by the question is identified by the token Data Structure, the receiver of the message is the GUD agent and the question is written in the language PROLOG. A message in Figure 6 represents the response of the COA's question. In this message, the KQML performative is Tell, the sender is the GUD, the receiver is to the COA, and the content of the message is "L_1".

Figure 7 shows the current version of CITS which can be optionally used in a collaborative knowledge environment, in which two or more learners share their knowledge. The present system is built in Visual J++ and operates under Windows 2000. The presented version shows an interaction between two learners using CITS. The interface of the current version provides learners with two functions. One of them is a discussion window that permits communication among learners. And the second one is a whiteboard windows where the learners can draw anything related to their discussion

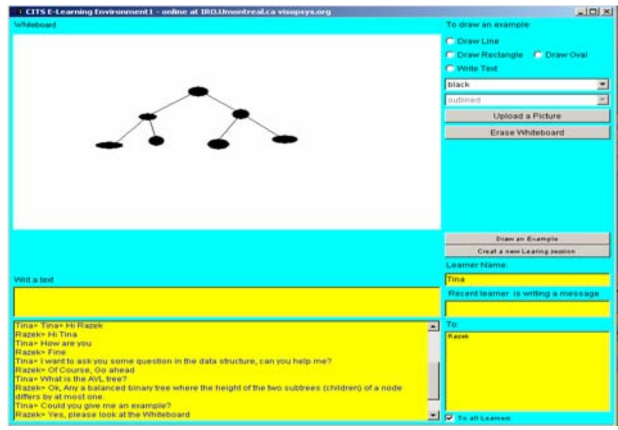

Figure 7 CITS User Interface

7. CONCLUSION & FUTURE WORK

We have proposed a new architecture, based on a multi-agent technique, to improve intelligent distance learning environments. We defined the standards of a confidence agent in ITS by which an ITS provides more intelligent and acceptable learning and teaching. To promote some of these standards, we presented a new system called Confidence Intelligent Tutoring System. The proposed system can learn from either the learner or the Internet.

Using a combination of learner's knowledge level, learning style, and personality traits, the proposed system allows two or more groups with different learning style and different personality traits to communicate with each other. This way not only provides the group with a good learning environment but also keeps personal information from others.

A first version of this architecture has been implemented. We must still implement, improve, and study some aspects. One opportunity for improvement would be the way in which knowledge is represented. We use XML language to represent knowledge, and employ XSL-Templates to adapt presentation according to need.

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