Dynamic Case-Based Reasoning Based on the Multi-Agent Systems: Individualized Follow-Up of Learners in Distance Learning

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Abstract. In a Computing Environment for Human Learning (CEHL), there is still the problem of knowing how to ensure an individualized and continuous learner's follow-up during learning process, indeed among the numerous methods proposed, very few systems concentrate on a real time learner's followup. Our work in this field develops the design and implementation of a Multi-Agent Systems Based on Dynamic Case Based Reasoning which can initiate learning and provide an individualized follow-up of learner. When interacting with the platform, every learner leaves his/her traces in the machine. These traces are stored in a basis under the form of scenarios which enrich collective past experience. The system monitors, compares and analyses these traces to keep a constant intelligent watch and therefore detect difficulties hindering progress and avoid possible dropping out. The system can support any learning subject. To help and guide the learner, the system is equipped with combined virtual and human tutors.

Keywords: Distance Learning, Dynamic Case-Based Reasoning, Intelligent Tutor, Multi-Agent Systems, Scenarios, Traces.

1 Introduction

The CEHL is a computer tool which offers learners another medium of learning. Indeed it allows learner to break free from the constraints of time and place of training. They are due to the learner's availability. In addition, the instructor is not physically present and training usually happens asynchronously. However, most E-

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learning platforms allow the transfer of knowledge in digital format, without integrating the latest teaching approach in the field of education (e. g. constructivism, [13], ...). Consequently, in most cases distance learning systems degenerate into tools for downloading courses in different formats (pdf, word ...). These platforms also cause significant overload and cognitive disorientation for learners. Today, it is therefore necessary to design a CEHL that provides individualized follow-up to meet the pace and process of learning for the learner, who thus becomes the pilot of training. Our contribution in this field is to design and implement a computer system (i. e. intelligent tutor) able to initiate the learning and provide an individualized monitoring of the learner.

Solving these problems involves first, to understand the behavior of the learner, or group of learners, who use CEHL to identify the causes of problems or difficulties which a learner can encounter. This can be accomplished while leaning on the traces of interactions of the learner with the CEHL, which include history, chronology of interactions and productions left by the learner during his/her learning process. This will allow us the reconstruction of perception elements of the activity performed by the learner. According to Marty and Mille [10] the digital traces of interactions represent a major resource customization CEHL.

We propose a system able to represent, follow and analyze the evolution of a learning situation through the exploitation and the treatment of the traces left by the learner during his/her learning on the platform. This system is based, firstly on the traces to feed the system and secondly on the reconciliation between the course of the learner (traces in progress) and past courses (or past traces). The past traces are stored in the form of scenarios in a database called ”base of scenario”. Recently, several research works have been focused on the dynamic case based reasoning in order to push the limits of case based reasoning system dealing with situations static, reactive and responsive to users. All these works are based on the observation that the current tools are limited in capabilities, and are not capable of evolving to fit the non-anticipated or emerging needs. For example, few CBR systems are able to change over time the way of representing a case [12]. We propose a system, which analyzes the traces of learners in a continuous way, in order to ensure an automatic and a continuous monitoring of the learner. Our work in this field develops the design and implementation of a Dynamic Case Based Reasoning founded on the Multi-Agent Systems (MAS).

The rest of this paper is organized as follows: In the second section, we give a general introduction of E-earning and intelligent tutoring. The third section is devoted to the presentation of the design and implementation of our approach. So we will introduce the general architecture of the system. In section four, we will describe the approach of Multi-Agent Case Based Reasoning. In the following section, we will propose the description of our approach Multi-Agent Dynamic Case Based Reasoning. Finally, we will give the conclusion and our perspectives.

2 Intelligent Tutor and Distance Learning

Intelligent Tutoring Systems (ITS) are computer systems designed to assist and facilitate the task of learning for the learner. They have expertise in so far as they know the subject matter taught (domain knowledge), how to teach (pedagogical knowledge) and also how to acquire information on the learner (learner representative).

There is much research concerned with the design and implementation of computer systems to assist a learner in learning. There are, for example, tutors or teaching agents who accompany learners by proposing remedial activities [5]. There are also the agents of support to the group collaboration in the learning [3] encouraging, the learners participation and facilitating discussion between them. Other solutions are based on agents that incorporate and seek to make cooperation among various Intelligent Tutoring Systems [2]. The Baghera platform [18], which is a ”distance” CEHL exploits the concepts and methods of Multi-Agent approach. Baghera assists learners in their work solving exercise in geometry. These tools of distance learning do not allow an individualized, continuous and real-time learners follow-up. They adopt a traditional pedagogical approach (behaviorist) instead of integrating the latest teaching approaches (constructivism [13], [17]). Finally, given the large number of learners who leave their training, the adaptation of learning according to the learners profile has become indispensable today. Our contribution consists in proposing an adaptive system to ensure an automatic and a continuous monitoring of the learner. This monitoring is based on cases (dropping out, difficulties) past and similar.

3 General Architecture of our System

One of the main objectives of the individualized monitoring of the learner is to envisage, to anticipate and to reduce the number of dropping out, which makes us seek a flexible and adaptive solution [4]. The complexity of the situations to be treated leads us to choose an approach based on a MAS, able to cooperate and coordinate their actions to provide a pedagogical adaptation for the learners profile. We reconcile the problems of the analysis of the traces left by the learners activity in CEHL, and the decision support systems, able to represent, follow in real-time and analyze the evolution of a dynamic situation. Such a system must represent the current situation, take into account the dynamic change of the current situation, predict the possible evolution of this situation, and react depending on the particular situations and the learners profiles. This can be done by using past situations which consequences are known. It is then a question of reasoning by analogy. This type of reasoning can allow solving new problems, using already solved problems available in memory. The system we propose, allows to analyze the learners course (trace) in order to anticipate a possible dropping-out. The learning activities past traces will be the source of knowledge for the learning adaptation process, they are stored in a database called ”base of scenarios”. Each scenario contains all determining aspects in its development, i.e, the facts that have played an effective role in the way the events proceeded. The analysis of the current situation must be continuous and dynamic. Indeed, the target case is a plot that evolves, therefore the system must take this incremental evolution into account.

The general architecture of our system consists of the three following components (Fig. 1):

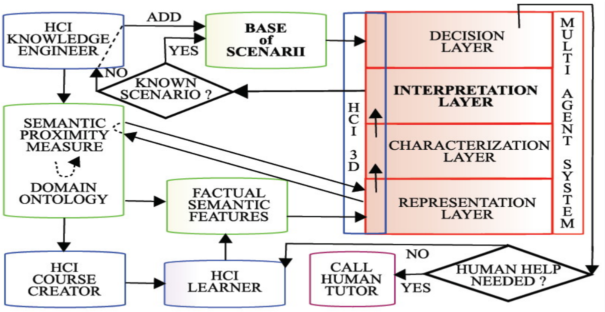

Fig. 1 General architecture of our intelligent tutor system

- The graphical interfaces for learners (who are the users for whom the system is developed), for course designers (who must structure the teaching contents) and finally the developers (Human and Computer Interface ”HCI” knowledge engineer for the knowledge module, and a tree Dimension Human and Computer Interface ”3D HCI” for the behavior of the Multi-Agent Systems);
- The Knowledge module containing: Base of Scenarios, Factual Semantic Features, Semantic Proximity Measure and Domain Ontology;
- The hierarchical MAS with four layers.

4 Multi-Agent Case Based Reasoning

Case-Based Reasoning (CBR) is an artificial intelligence methodology which aims at solving new problems based on past experience or the solutions of similar previous problems in the available memory [7]. The solved problems are called source cases and are stored in a database (called a case-base or base of scenarios). The problem to be solved is stored as a new case and is called target case. The systems based on the case-based reasoning can be classified into two categories of applications [9]: Applications dealing with situations static (i. g. CHIEF [6] and Creek [1]) and Applications with dynamic situations (i. g. REBECAS [9]), for more details on the subject, the reader may refer to [9].

The Multi-Agent Systems based on case based reasoning are used in many applications areas. we can distinguish two types of applications:

- The Multi-Agent Systems in which each agent uses the case based reasoning internally to their own needs (level agent case based reasoning). For this systems, each agent is able to find similar cases to the target case in their own case base, also able to accomplish the other steps of CBR cycle (i. g. the system AMAL [15] for Multi-Agent arguments, CCBR for personalized route planning [11], and MCBR [8] for distributed systems).

- The Multi-Agent Systems whose approach is a case based reasoning (level Multi-Agent Case Based Reasoning). For this applications, the Multi-Agent Case Based Reasoning System distribute the some/all steps of the CBR cycle (Representation, Retrieve, Reuse, Revise, Retain) among several agents. This type of approach might be better than the first. Indeed, the individual agents experience may be limited, therefore their knowledge and predictions too, thus the agents can benefit from the other agents capabilities, cooperate with each other for better prediction of the situation (i. g. the PROCLAIM [16] in argumentation field, and CBRTEAM [14] in a parametric design task).

5 Multi-Agent Dynamic Case Based Reasoning

Our problem is similar to the CBR for dynamic situations. Indeed, the traces left by the learner during the learning session evolve dynamically over time; the case-based reasoning must take into account this evolution in an incremental way. In other words, we do not consider each evolution of the traces as a new target. The CBR which we propose offer important features: (1) It is dynamic. Indeed, we must continually acquire new knowledge to better reproduce human behavior in each situation; And (2) It is incremental, this is its major feature because the trace evolves in a dynamic way for the same target case. The main benefits of our approach are the distributed capabilities of the Multi-Agent Systems and the self-adaption ability to the changes that occur in each situation.

Each action of the learner is represented by a data structure called semantic features that are supported by factual agents. The course of the learner is well represented by a set of trace agents [4]. Therefore, the various actions of the learner (learner traces) can be represented as a collection of semantic features. These will feed the representation layer (Layer 1). The role of this layer is to be both, a picture of the current situation being analyzed and to represent the dynamics of its evolutions over time. The goal of the characterization layer (Layer 2) is to provide a synthetic vision of the organization of agents of the representation layer by classifying them in several subsets according to their activity degrees. A part of the target case in the dynamic and incremental case-based reasoning is developed by this layer. The interpretation, or prediction, layer (Layer 3) will associate the agents characterization subsets layer with a scenario. The interpretation agents also allow to update the system knowledge by the learning of new cases. In fact, they store and manage new scenarios [4]. The decision layer (Layer 4) selects similar scenarios in the base of scenarios and chooses one to propose to the learner. For each particular situation, the decision agents can react differently depending on the learners profile concerned, for example, deciding to initiate a communication session with a learners experiencing difficulties. The human tutor is needed if the system detects a learning situation requiring his/her intervention.

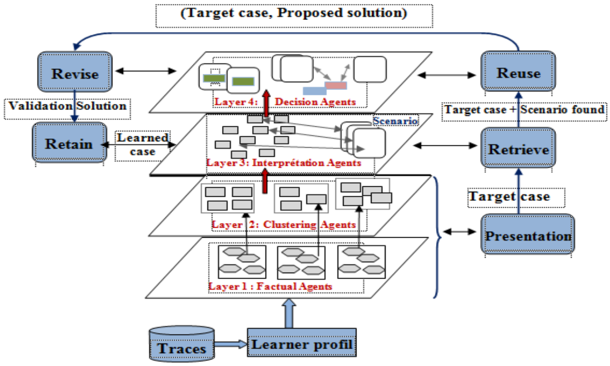

Fig. 2 Dynamic CBR cycle in our approach

The CEHL personalization is primarily depending on the ability to produce relevant and exploitable traces of the learners activity (for more details concerning the learner's traces, the reader may refer to [19]). These traces allow us to describe and to document the learners activity. In the current uses of the traces for the CEHL, collected situations are contrasted: from ”we take what we have in well specified formats, what is called the logs” to ”we scrupulously instruments the environment to recover the observed controlled and useful for different actors (learner and tutor)”. The first step consists of modeling the raw data contained in the log file. It is necessary to be able to collect files of traces containing at least, the following elements: time for the start date of the action, codes action which consists in codifying the learners actions and learner concerned.

6 Conclusion and Future Work

Our system allows connecting and comparing the scenario found (current situation) to past scenarios that are stored in a database. The continuous analysis of information coming from the environment (learners traces) makes it possible to suggest to various actors (learners and tutor) possible evolutions of the current situation. The Multi-Agent architecture that we propose is based on four layers of agents with a pyramidal relation. We have presented systems based on Dynamic Case Based Reasoning and we have also clarified that the CBR-based applications can be classified according to the study area: CBR for static situations and CBR for dynamic situations. In our situation, we have used a dynamic case based reasoning with important features. Indeed, the current situation (target case) is a trace that evolves; the case based reasoning must take into account this evolution incrementally. In other words, it shouldnt consider each evolution of the trace as a new target case. Our future work consists in realizing a comparative study between our system and other tools. In addition, by giving a comparison of different existing similarity measures between sequences, We will propose our new similarity measure, such as: The Inverse LCSS (ILCSS).

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