Cultivating Intelligent Tutoring Cognizing Agents in Ill-Defined Domains Using Hybrid Approaches

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Abstract: Cognizing agents are those systems that can perceive information from the external environment and can *adapt* to the changing conditions of that environment. Along the adaptation process a cognizing agent perceives information about the environment and generates reactions. An intelligent tutoring cognizing agent should deal not only with the tutoring system's world but also with the learner-it should infer and predict new information about the learner and tailor the learning process to fit this specific learner. This paper shows how intelligent tutoring cognizing agents can be cultivated in ill-defined domains using hybrid techniques instantiated in the two example agents AEINS-CA and ALES-CA. These agents offer adaptive learning process and personalized feedback aiming to transfer certain cognitive skills, such as problem solving skills to the learners and develop their reasoning in the two ill-defined domains of ethics and argumentation. The paper focuses on the internal structure of each agent and the reasoning methodology, in which, the cognizing agent administration and construction along with the pedagogical scenarios are described.

Keywords: Ill-defined domains, ethics, argumentation, cognizing agents, student modeling

1. Introduction

Ill-defined domains always pose a rich research environment because of the challenges they provide. These domains are characterized by having problems in which there is no single right or wrong answer to problems nominally of the same type [8], having no clear or complete domain theory for determining a problem's outcome and testing its validity, exhibit ill defined task structure [35] and can involve more than one aspect that inter-correlate to different degrees with each other [10]. This contrasts to well defined domains that have defined structure, which can be clearly modeled and make it easy to unambiguously classify problem solutions as correct or incorrect. The main aspect characterizes ill-defined domains is that learning requires not only acquiring knowledge but also a change in the way a person thinks [11, 12]. This is manifested in domains like ethics and argumentation.

Ethics and argumentation domains are complex ill-defined as they contain numerous knowledge elements and relations by which problem analysis in both domains has many controversial solutions with no clear procedure for evaluating these solutions [13, 35]. This requires different representation schemes for domain modeling and might require different techniques in tracking the learner and providing feedback. Although many Intelligent Tutoring System (ITS) strategies have been employed in ill-defined domains and have proven successful in past studies [10, 14, 18, 26, 28, 34]. Intelligent tutoring cognizing agents role in these domains have not been explored enough yet.

Intelligent tutoring cognizing agents offer a useful platform that can be used to teach in ill-defined domains. It perceives knowledge from the tutoring system's world and the user. Intelligence can be reflected in the way the agent reacts with the environment and how it adapts to the changing environment. This manifests in the way the cognizing agent interacts with the user, infers new information about the user and updates his /her profile and finally, the agent's response to the tutoring world (environment).

In this paper, we present intelligent tutoring cognizing agents developed in the ethics and argumentation domains instantiated in the two example agents AEINS-CA and ALES-CA developed in the ethics and argumentation domains. This paper focuses on the approaches each of the systems use in order to address the challenges present in the ethics and the argumentation domains, such as knowledge representation, tracking the learning process, and providing personalized feedback. Even though both agents are applied in ill-defined domains, the internal structure of each agent is different because of the nature of the targeted domains. The paper also provides suggestions on how the developed approaches can be transferred to other ill-defined domains.

3 Cognitive Reasoning Using Cognizing Agent and Hybrid Approaches

Cognitive reasoning in AI-systems is the process of realization based on vague knowledge by analyzing and observing the inferred data and generating the hypotheses. It can be presented as the motion from ignorance to knowledge [29]. Designing and building intelligent cognitive systems in ill-defined domains is a challenging research problem since it deals with uncertain clear scenarios for problem solving. Several strategies have been proposed in order to overcome this challenge. For example, Model Tracing (MT), Constraint-Based Modeling (CBM), and Expert System Approach are examples of these strategies [35]. However, each strategy has its own limitations. Accordingly, both AIENS-CA and ALES-CA exploit hybrid approaches to act as cognizing agents to reveal concise analysis and cognitive reasoning. The next subsections introduce the targeted domains and describe how both AEINS-CA and ALES-CA satisfy the requirements of a cognizing agent utilizing hybrid approaches in order to achieve and cultivate the prospected tutoring services.

3.1 ALES-Cognizing agents (ALES-CA)

This section defines the ill-defined argumentation domain highlighting the challenges exist in this domain. It also presents the architecture of ALES-CA and explains the use of hybrid AI approaches utilized to serve the design and the implementation of this cognizing agent.

3.1.1 Argumentation as an ill-defined domain

Argumentation is a vital skill in many aspects of life. Teaching argumentation and learning to argue are important in real life for humans' debates understanding. More over teaching argumentation is a very important educational goal that helps students to **hone** their argumentation skill. This skill is extremely valuable in the educational field as it reflects the learner's ability to outline a claim in a logical and convincing way and provides supportable reasons for the claim, as well as identifying the often implicit assumptions that underlie the claim. However, many educational technology systems teach argumentation by having students create or reconstruct arguments in diagrammatic form [30, 31, 32, 33]. Whereas, these educational argumentation systems, often attempt to analyze the diagrams in order to provide feedback based on structural relations in diagrams or analyze arguments using machine learning and text analysis techniques. They have not played an important role in assessing the student's performance, which is typically measured in a pre/post tests. It would be very helpful if these systems conveyed information about the learning process or the performance of the students.

ALES-CA provides different assessment methods, pre/post tests and diagrams that measure the students' performance associated with personal feedbacks. It integrates different data mining techniques and AI approaches in order to have an intelligent tutoring system that teach argumentation based on specific argumentation schemes. ALES-CA offers several tutoring services in argumentation filed such as : i) an argument classifier agent that retrieves the most relevant results to the subject of search, ii) a cognitive assessment to the learner's knowledge during the different learning phases, iii) a graphical representation for the learner's performance history, iv) two different scenarios for teaching argumentation skills.

3.1.2 The Architecture of ALES-CA

Cognizing agents have three main units; the ***sensing/perception*** unit, the ***interiorisation*** unit, and the ***reasoning*** unit. The sensing/perception unit main task is to transfer the information from the learner to the agent. This information is transferred, in the form of external knowledge and data, from the learner through the presentation model. After then, the ***interiorisation*** unit receives the external knowledge and transforms it into internal data format (relational records and attributes) to be accessed by the reasoning unit. The ***reasoning*** unit has two subunits, the control subunit and the reasoner subunit. The control subunit manages the activities of the cognizing agent. For example, controls the switching between the distinguished learning modes of the agent. The reasoner subunit includes the reasoning mechanisms, which allows the agent to reason about the external environment including the learner. In summary, cognizing agents sustain the interactions with the learner and model his/her cognitive activities [29].

ALES-CA is a software agent for teaching and improving argumentation skills. It integrates the Argumentation Interchange Format Ontology (AIF) together with hybrid approaches for supporting tutoring services. These approaches combine data mining, model tracing and expert system techniques in order to manage a highly structured arguments repository. ALES-CA adapts the general cognizing agent architecture as shown in Fig.1 to its needs. The perception unit makes use of a GUI to interact with the learner using either questions and answers interaction or diagrams in the form of textual trees. The interior level contains a domain model and a learner's model. The domain model is represented in the form of an RADB that contains the expertise's pre-analyzed arguments based on Walton theory of argumentation using the AIF ontology [27] where, contexts are analyzed based on specific schemes into conclusion, premises and set of critical assumption. The learner's model stores details about the learner's current problem-solving state and the long term knowledge progress, which is essential for future learner's performance evaluations.

The other important component of ALES-CA is the reasoner unit that incorporates pedagogical and teaching models. The pedagogical model contains the parser unit [3], which divides the input statement S, received from the learner, into set of tokens. These tokens in turn, are reduced to a set of significant keywords and sent to the classifier agent unit. The classifier agent mines the RADB repository using different mining techniques in order to direct the search process towards hypotheses that are more relevant to learner's subject of search, and add flexibility to the retrieving process, by offering different search methods: priority search, rule extraction search, and general search [2, 3, 4].On the other hand, the teaching model monitors the learner actions, guides the learning process and provides personalized feedback. The model starts its role when the classifier agent sends the document selected by the learner. If the learner is in the learning phase, the document is presented associated with the corresponding analysis. On the other hand, if the learner is in the assessment phase, the learner is able to do his own analysis with the guidance of the teaching model.

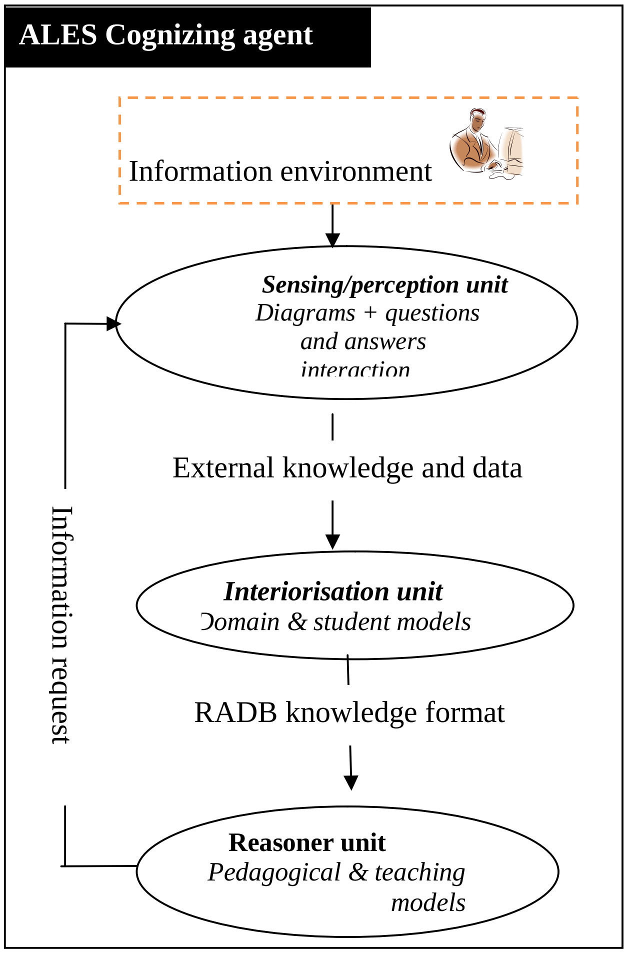

Fig. 1. General representation of the cognizing agent

3.1.3 Learning Process in ALES-CA

ALES-CA is designed to administrate and offer the following tutoring services i) personalized search, ii) pre-evaluation for the learner in order to show the suitable contexts that the learner can analyze two learning scenarios, a) learning by search and b) learning by assessment., iii) provide both formative and summative feedbacks based on the learners choice, these feedbacks guide the learner and limit his/her mistakes during the learning by assessment phase, and iv) predict the learner's performance level using graphical reports by monitoring and analyzing his/her historical performance. In the following we will focus on the personalized search, learning scenarios and feedback and assessments for the purpose of this paper.

i) Personalized Search

In order to retrieve the most relevant result to the subject of search, ALES-CA offeres three types of search**,** the ***Priority*** **search**, the ***General*** **search** and the ***Rule Extraction mining*** **search**. In all the offered search types, a hybrid approach between the case-based reasoning and machine learning approach has been implemented. For the ***Priority*** **search**, an adapted version of the AppriorTid Data mining technique has been used to mine specific parts of the pre-existing experts' arguments analyses based on the learner's choices. For the ***General Search***, the breadth first search technique has been used in order to encounter all nodes in the laying pre-existing experts' analyses trees. The ***Rule Extraction mining search***, it is a search technique in which argument trees analyses are encountered to discover all hidden patterns that coincide with the relation between some objects. These objects express a set of the most significant tokens of the user's subject of search. See [28] for more clarifications and examples.

ii) Learning Scenarios

a) ***Learning by search:*** In this scenario, the cognitive agent offers different contexts to the novice and asks him for the analyses. Then, the agent perceives the analyses and evaluates the novice level based on the pre-existed expert analyses for the same contexts. This phase is annotated as the pre-evaluation phase. If the novice level is below than specific threshold, the agent sends a message for the novice asking him to start the learning by search scenario. Otherwise the agent directs the novice to the learning by assessment scenario. In the learning by search, the agent offers a myriad of the pre-existing contexts associated with the experts' analyses graphs to the novice fingertips, where the novice can search and navigate freely using different types of search to learn about argument analyses. The agent offers this myriad and responses to the novice actions and requests by exploiting different data mining techniques, which return with the most relevant results to the subject of search using numerous criteria. For more details see [3, 29].

b) ***Learning by assessment:*** In this scenario, the cognitive agent asks the learner to choose either partial/ formative feedback or total/ summative feedback. Then, based on the learner performance history, the agent offers a new context, which has not been accessed before by the learner during the learning phases, and asks the learner to analyze it. During the analysis the agent performs two activities i) guides the learner's analysis by providing the specified feedback in order to compromise the learner's mistakes, ii) evaluates the learner's performance and records the performance ratio in the RADB. For more details see [29]**.**

iii) Feedback and assessments

In order to provide the cognitive assessment in the various learning phases, ALES-CA relies on the case-based reasoning method together with the SQL machine learning approach to compare the learners' solutions, which written in natural language, with the ideal solutions, which represent the pr-existing experts analyses. The system provides the gaudiness during the learning by assessment phase instantiated in the provided formative and summative feedback. These feedback aim to i) evaluate the analysis process rather than simply determining if the learner attained the correct analysis ii) suggest the next step to be taken by the learner. The comparing process is performed by dividing the learner's nature language statement into set of tokens and selecting the most significant tokens. After then, these most significant tokens are compared with the corresponding tokens in the experts' analysis for the same argument. Finally the error ratio is calculated and recorded, and the corrections are suggested, see [28] for more clarifications.

ALES-CA system facilitates the graphical presentation for the learner's performance history in the form of reports. Doing so requires knowledge acquisition for the monitored learner. This knowledge acquisition task is performed using numerous SQL statements that gather any historical data related to the learner and extract the needed information for the graphical presentation. The importance of that representative reports is to show the learner's progress and excavate the proper weakness points in his/her analysis skills [28].

3.2 AEINS-Cognizing Agent (AEINS-CA)

This section defines the ill-defined ethics domain, by highlighting the challenges exist in this domain. Then presents AEINS-CA architecture explaining how hybrid AI approaches have been utilized to serve the design- and implementation of this cognizing agent. In the following, we highlight the learning procedure and strategies employed by AIENS-CA and how the evaluation reflects the validity of those strategies in the designated paradigm.

3.2.1 Ethics Domain

Ethics is an important ill-defined domain; the development of skills of participation and responsible action is a fundamental part of citizenship and character building. Different approaches have been used in order to teach ethics in classroom environments such as role playing [16], interactive learning models [21] and brainstorming moral dilemmas [7]. These approaches allow situated learning where the learners are practicing the required concepts in a manner similar to that of the real world. They allow learners to express their character through the kind of choices they make. It has been shown that by providing a familiar context, students are able to better activate their prior knowledge [5].

Despite the effectiveness of these approaches, children differences in personalities and consequently in their strengths, weaknesses and needs raises the need for adaptive learning. Offering adaptive learning (customized learning process and personalized feedback) is always an advantage in education. Within the classroom environment this is very difficult to be addressed because of time and curriculum standard constraints [9]. We claim that the presence of an adaptive environment that allows the children to explore and act is adds to the effectiveness of education. In light of these findings, AEINS-CA architecture has been designed that integrates intelligent tutoring and AI techniques to teach in the ethics domain [11], see Fig. 2.

3.2.2 The Architecture of AEINS-CA

AEINS-CA is a software agent built as a bottom-up architecture in which various pieces of information from various models are connected together and reasoned about to serve a personalized learning process for each individual learner. AEINS-CA employs a hybrid approach via the combination of intelligent tutoring models, planning and semi-autonomous agents to provide, track and evaluate the student's learning process. The idea is to use analyzed moral dilemmas as story graph structures and to specify the decision points that reflect specified skills.

AEINS-CA presents the learner with new insights, and good models and examples, after which they could model their own behavior. It provides a customized learning environment and personalized feedback, in story context, to enable learners to test their own intuitions about certain moral values and to perform arbitrary experiments. In so doing it is believed that learners will better understand the nuances of the domain. The AEINS-CA main aim is to allow active learning through learning by doing which we consider a very effective leaning style in moral education. This is desired to be achieved through combining hybrid AI techniques in each of the levels presented in the cognizing agent architecture as shown in Fig. 2.

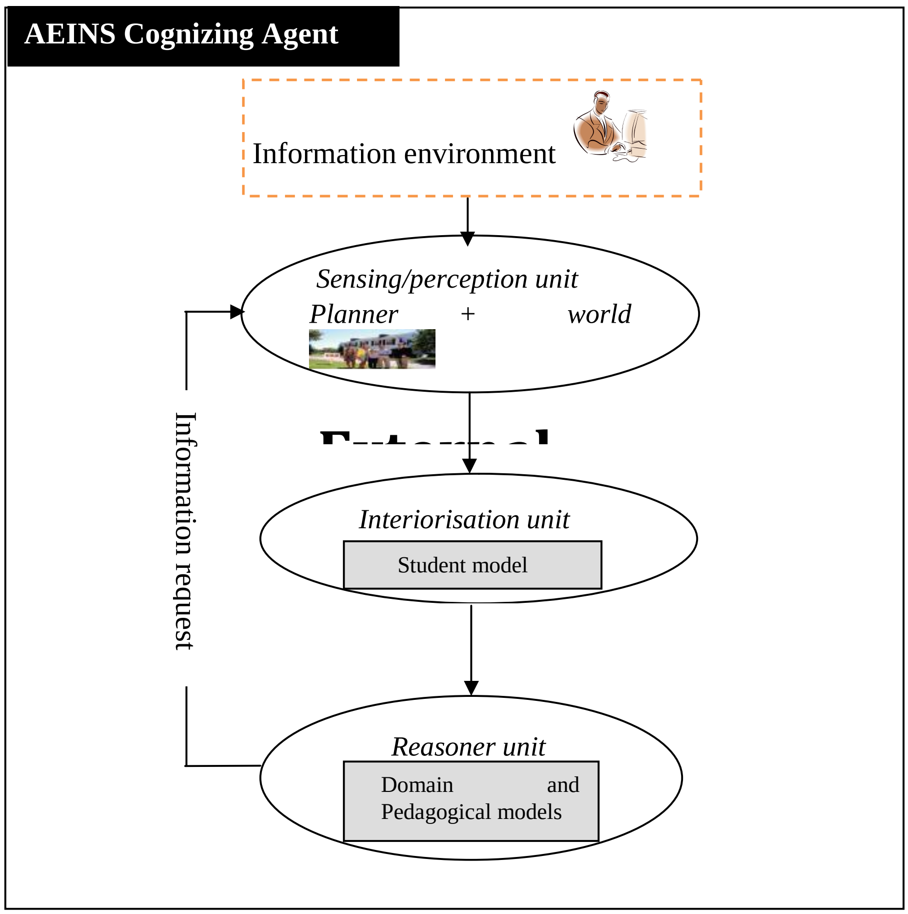

Fig.2: AEINS-CA architecture

AIENS-CO has a *percepting unit* as a GUI interface that handles the flow of information and monitors the interactions between the learner and the agent and vice versa. The *percepting unit* makes use of a planner that guides a group of semiautonomous agents to interact with the learner. The learner's interactions are passed to the *interiorisation level* to be transformed to internal structures and saved in the corresponding knowledge bases in real time. The *interiorisation level* makes use of a learner model by recording all the learner's interactions with the agent. The learner model considers many types of information, such as personal information, pre-test evaluation, and performance history. Adaptation in

AEINS-CA is a crucial property supplied through the learner's model. The learner's model is an overlay model represented in the form of rules associated with confidence factor, in the following form

skill(student name, skill name, level of mastery, confidence factor).

The information in the learner model is passed to the *reasoner unit* that makes use of two intelligent tutoring models; domain and pedagogical models. The pedagogical model is developed in the form of production rules that are used to give the system specific cognitive operations to reason about the learner and the teaching process. The use of rules enables assessing the learner's actions easily at run time. It is responsible for reasoning about the learner behavior according to the current student model and the domain model to decide on the next learning step. It adapts instruction (problem selection, problem difficulty level, learning topic, choice of activity, choice of help type, and availability of help) following a model of human tutoring expertise that balances motivational and cognitive goals. This information is passed to the *percepting unit* that delivers it to the planner to generate a plan and finally passes it to the semiautonomous agents to start executing this current step.

3.2.3 Learning Process in AEINS-CA

AEINS-CA supports inquiry-based learning by engaging learners in a game-like environment that accommodates non-playing characters who serve as pedagogical agents. The learning process starts by instantiating the learner's model through asking the learner some questions about the non playing characters in the game world. For example, Rana is popular, she doesn't lie and sincere, however Rana can cheat. Do you like to be Rana's friend? This question addresses the cheating immoral value and picks the learner mind about the way he feels towards this immoral value in an indirect way. If the learner agrees to be Rana's friend (Rana is a non-playing character) this implies that the learner might not be considering cheating as a bad moral. So this information is added to the learner's model and after then will be used by the pedagogical model to present the learner with certain moral dilemmas (teaching moments) that address cheating as an immoral value and consequences of exhibiting this kind of behaviour. The pedagogical agents adopt the voice of Socrates following the Socratic Dialogue as the teaching pedagogy. The Socratic Dialogue is powerful because of its capability of forcing the learner to face the contradictions present in any course of action that is not based on principles of justice or fairness.

The planner is used to move the story forward from the current situation to another desired situation that can act as pre-settings for a teaching moment to begin. Once the teaching moment starts, the story of the teaching moment unfolds based on the learner's interactions. For example, in the cheating dilemma the story might end in a good way if the student's actions reflect his understanding that cheating is immoral and good persons do not exhibit cheating, in addition to their awareness of the consequences of adopting this kind of act as such leading to troubles. On the contrary, the story might not end nicely in order to reveal the consequences of cheating. For example, the learner's mum blaming him for cheating and bans him from the holiday trip.

The empirical study reflects the impact of these endings on the learners and how by being incorporated in these teaching moments they were able to reflect on the events and discover new knowledge by themselves. They were also able to build a social relationship with the other agents. For example, they wanted to give advises to one of the agents who seems always lie. The learning process continues based on the learner's model with either providing new teaching moments that address other morals or the same moral if the learner's actions still reflect his misunderstanding. This is mainly a task for the pedagogical model to do relying on the domain model and the current learner model.

The evaluation of the learning process is a continuous process in AEINS-CA that can provide either formative or summative feedback. The formative feedback can be delivered instantly after a specific action done by the learner. For example, if the learner's choose to help a friend to cheat in the exam, another agent could blame him for doing this highlighting the consequences of such action. Summative feedback is provided at the end of the teaching moment. For example, if the learner's model reflects an understanding for the concept being learnt, the story ends in a good way where the num will reward the learner by praising his attitude. The learning process ends when the learner's model shows an understanding for all the concepts needed to be learned.

4. Evaluation of ALES-CA and AEINS-CA

Analytical evaluation for both systems has been done through intrinsic evaluation that checks the implicit goals embodied by aspects of the design, and makes value judgment about these goals. It has been found that the rule representation currently used allows the appropriate level of interaction between the models. Most importantly is the systems' ability to correctly identify the participants' misconceptions and provide the suitable feedback, for instance the pedagogical models are able to decide about the next appropriate educational step based on the current student model, where the presence of the student model allows the required personalized learning process according to the learner's needs. On the other hand, without such model, the teaching scenario is presented in a specified sequence for all learners whatever the differences between them. With this evidence, we can say that the systems' models are able to fulfill the design aims.

In the future, empirical evaluation is planned to assess the educational outcomes. In designing the study, it is determined that the best way to approach it is to rely on a qualitative evaluation method which produces a description, usually in non-numeric terms ideal for eliciting users' thoughts. This will allow the participants to express their program experiences and judgments in their own terms. The resulted data would consist of verbatim quotations with sufficient context to be interpretable and can lead to quantifiable results.

5. Related Work

Currently, many educational systems that use narrative and tutoring techniques try to balance the evolved narrative and the education process by tailoring the educational materials in the narrative. Some systems exhibit narrative limitations for example, ELECT BILATE [15] and BAT ILE [25]. The former uses a limited scripted narrative in order to preserve the educational targets; this strategy limits the freedom of the learner [20]. The latter uses narrative in the tutor student direction, but not vice versa. In other words, the effect of the learner's actions is not obvious in the narrative. Other systems lack the presence of a student model that has proven its importance in providing an adaptive learning process such as FearNot! [6] and Crystal Island [17]. Other systems refer to the presence of a student model without making it clear how it is used, how it is updated and how it affects the learning path. For example, in Mimesis [22] or as in TLCTS [23] it was obvious that the learner's actions affects the agents reactions but not obvious how it affects the learning process and/or the choice of the next educational step. These shortcomings have been tackled by AEINS, where it mixes continuous planning and branching planning approaches.

The continuous planning sustains the freedom of the player and allows him to affect the story unfold and feel control over the environment. The branched narrative helps in preserving the educational goals and allows the cognitive tutor to follow and assess the learner. AEINS also incorporates a student model that helps in providing an adaptive learning process.

Recently, in argumentation field, a number of argument mapping tools [19, 24] have been developed to foster debate among students about specific argument, using diagrams for argument representation. However, the data mining and artificial intelligence influence, which needed to guide the student to understand the relation between scientific theories and evidence, and refines his argument analysis ability, are missing in these tools. In order to overcome this, I. Rahwan presents the ArgDf system [27], through which users can create, manipulate, and query arguments using different argumentation schemes. Comparing ArgDf with ALES-CA, both of them sustain creating new arguments based on existing argument schemes. However, the ArgDf system guides the user during the creation process based on the scheme structure; the user relies on his efforts and his background to analyze the argument. Where ALES-CA not only guides the user by the scheme structure but also by crucial hints devolved through two types of feedbacks. Accordingly, the analysis process is restricted by comparing the contrasting reconstruction of the user's analysis and the pre-existing one. Such restriction helps in refining the user's underlying classification. In the ArgDf system, searching existing arguments is revealed by specifying text in the premises or the conclusion, as well as the type of relationship between them. Whereas in our hybtid approach, searching the existing arguments is not only done by specifying text in the premises or the conclusion but also by providing different strategies based on different mining techniques in order to: refine the learning environment by adding more flexible interoperability, guarantee the retrieval of the most convenient hypotheses relevant to the subject of search, facilitate the search process by providing a different search criteria.

6. Discussion

Lately, different researches have proposed different strategies for reasoning in ill-defined domains. Model tracing (MT), constraint-based modeling (CBM), and expert system approach are examples of these reasoning strategies. However, these strategies suffer from several limitations with respect to ill-defined domains. Such as, the absence of clear strategy for finding solutions, the lack of the suitable help that suggests the next step for the learners, and the missing of the inference which provides the explanation for the learners.

This paper presents AEINS-CA and ALES-CA as two cognizing agents in the ill-defined ethics and argumentation domains. These systems have used the hybrid approaches in order to make use of their individual strengths and overcome the individual limitations. AIENS-CA is an intelligent cognizing agent that offers an enquiry based learning that allows the learner’s to change and revise their mental models (mental models usually contain minimal information described as a set of well-defined, highly organized knowledge) about specific concepts based on their interactions with specific moral dilemmas (teaching moments). AEINS-CA utilizes a hybrid approach in order to capture the required cognitive practices. It incorporates intelligent tutoring, planning and semi-autonomous agents. All techniques have been seamlessly combined in order to provide an adaptive learning process tailored for individual learners. Intelligent tutoring provides various tutoring models, such as the domain and pedagogical models. Most importantly it allows building a learner’s model that is the key in the adaptation process. Planning offers the dynamic story generation for different users and even for a single learner over few turns. Finally, semi-autonomous agents act as an attractive element for the learner. They engage the learner socially and sometimes emotionally. The agents successfully perform their pedagogical role which highly enhances the learning process.

The second cognizing agent presented in this paper is ALES-CA that considers the argumentation field as one of the ill-defined domains. It uses the hybrid approaches in order to cultivate agent performance, results and highly enhance the offered learning processes.
It incorporates the Data mining and the intelligent tutoring techniques in the argumentation domain aiming to (i) minimize the learners dispersion in the different learning phases by retrieving the most relevant results to the subject of search, (ii) provide the suitable help and suggest the next step for the learners by offering different types of feedbacks, (iii) offer the explanation for the learners by tracing his/her solutions during the learning phases and presenting an illustrative reports that indicate the mistakes compared with the expert pre-exist solution.

ALES-CA enjoys certain advantages over others in the same field, where (i) a relevant and convenient result is assured to be obtained especially when the search statement is in this form: "the destructive war in Iraq", (ii) different representative reports that represents the learner's progress can easily be extracted, (iii) two different types of feedback are provided to guide the learners during argument learning process. Moreover, ALES-CA is capable of producing representative reports about the learner analysis history. These reports can excavate the proper weakness points in the learners' analysis skills. On the other hand, ALES-CA handles special types of arguments, in which only one scheme is used in the analysis process. So, if the context is much bigger and needs more than one scheme in its analysis, ALES-CA cannot be used. Moreover, ALES-CA cannot detect the synonyms in the learner's analysis comparing to the pre-existing analysis and considers them as errors.

Generally, the architecture of AEINS-CA and ALES-CA enjoy the extendibility feature and are general enough to be applied to other ill-defined domains. They could be applied in domains where stories are needed as the educational medium to transfer tacit knowledge such as ethics, history or cultural studies. In addition to any domain that require not only knowledge acquisition but also a change in the person ideas.

7. Conclusion

This paper presents the general architectures of intelligent tutoring cognizing agent (ITCA) in ill-defined domains. This has been instantiated in the two example agents AEINS-CA and ALES-CA. These agents consider the ambiguous poorly defined nature of ill-defined domains. They used hybrid approaches for the entire cognizing agnets' models in order to suit the target domains, ethics and argumentation. These agents are able to offer adaptive learning processes and personalized feedback that allow the transfer of the required skills to the learners and help them to develop their reasoning skills. Intrinsic evaluation is provided that shows the validity of the interaction between the modules of AEINS-CA and ALES-CA and the need for qualitative evaluation has been verified.

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