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Orchestrating an adaptive intelligent tutoring system: towards integrating the user profile for learning improvement

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Abstract

An intelligent tutoring system aims to provide immediate and customized instruction and feedback to learners. In this context, existing tutoring systems have limitations in the areas of dialogue, feedback and emotion-motivation, which are important elements in the learning process. These aspects are related with the learner abilities, capacities, and motivations. To overcome these limitations, we propose to model the user characteristics that are involved in the learning process and in the human-machine interaction. In this paper we present a proposal to consider an integral user profile in order to gain effectiveness and to achieve more adaptability to the learner.

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Keywords: intelligent, adaptive, tutoring system, integral user profile, software engineering.

1. Introduction

Traditional instructional methods teach learners presenting facts and concepts followed by tests (Ong & Ramachandran, 2003). These methods are used for exposing learners to large amounts of information and testing their recall. However, they often impart "passive knowledge" that learners can recall but may not apply correctly when needed. With the proliferation of information technologies, nowadays, those methods have been obsolescent. Using technology to assists teaching was a solution. Teaching tutoring systems that act as personalized tutors became a popular media in past decades. By today, there are many environments for learning, varying from open online environments and Internet searching engines to desktop tools. Based on this, we have the following question: Is a personalized tutoring system an effective tool for improving learning? Individual

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tutoring is perhaps the first instructional method; it dates back at least to Socrates and the Socratic method (Koedinger & Corbett, 2006). In addition, one-to-one tutoring by expert human tutors has been shown to be much more effective than typical one-to-many classroom instruction (Bloom, 1984). Furthermore, computers are a familiar sight in classrooms (and outside) in the twenty-first century, and technology has been used to streamline many educational tasks, so that, we can continue improving the usefulness of computer-based tutoring systems.

Since three decades ago, researchers demonstrated that students who receive one-on-one instruction perform two standard deviations better than students in traditional classrooms (Ong & Ramachandran, 2003). However, in most cases, it is too much expensive to dedicate one instructor for each student. Then, the challenge is how to take the subject matter expertise and the teaching skills of the best instructors or mentors and encode them in a software system to provide the benefits of intelligent, one-on-one instruction cost-effectively systems (Ong & Ramachandran, 2003). In order to achieve this objective, from two decades ago many efforts have been made in developing intelligent tutoring systems (ITS). Other types of implemented systems are: computer assisted instruction (CAI) (Hall, Hughes & Filbert, 2000; AlSultan, Lim, MatJafri & Abdullah, 2006; Child, 1995; Fazelian, Saadatmand & Rad Saadat Gholi, 2005), cognitive tools (Beaumie & Reeves, 2007), adaptive intelligent tutoring systems (AITS) (Phobun & Vicheanpanya, 2010).

An ITS is defined as a computer system that aims to provide immediate and customized instruction or feedback to learners (Psotka & Mutter, 1988), usually without intervention from a human teacher. This context encompasses any computer program that contains some intelligence and can be used in learning (Psotka & Mutter, 1988). The main goal of ITSs is enabling learning in a meaningful and effective manner by using a variety of computing technologies (Ong & Ramachandran, 2003). However, in most cases, it is much too expensive to dedicate one instructor for each student.

Cognitive tools are technologies that learners interact and think with in knowledge construction, designed to bring expertise to the performance as part of the joint learning system (Beaumie & Reeves, 2007). Cognitive tools are generalizable computer tools that are intended to engage and facilitate cognitive processing. Cognitive tools refer to learning with technology as opposed to learning through technology.

CAI is a self-learning technique, usually offline/online, involving interaction of the student with programmed instructional materials (Hall, Hughes & Filbert, 2000; AlSultan, Lim, MatJafri & Abdullah, 2006; Child, 1995); a computer is used to present the instructional material and monitor the learning that takes place. CAI programs use tutorials, drill and practice, simulation, and problem solving approaches to present topics, and they test the student's understanding. CAI uses a combination of text, graphics, sound and video in enhancing the learning process (Fazelian, Saadatmand & Rad Saadat Gholi, 2005). In the form of a tutorial system, activity includes both the presentation of information and its extension into different forms of work, including drill and practice, games and simulation.

Adaptive Instructional Systems (AIS) emphasize that the effectiveness of instructional systems can be improved by incorporating algorithms that adapt instruction to individual capacities and differences (Ong & Ramachandran, 2005). These systems pretend to include other user attributes, such as cognitive styles, personality types, mental and emotional state, student experiences, and learning style. Most of the AIS models specify the data and algorithms required to assess (or estimate) these student attributes and apply these estimations to make better instructional decisions. Over AISs there is one more level of specialized systems such as AITS, which are systems that reach for adapting learning environments to student behavior. AITSs allow knowledge to be stored in such a way that is not only independent of the knowledge domain, but also supports the storage of transfer knowledge relationships and prerequisite knowledge relationships (Phobun & Vicheanpanya, 2010).

Even though this diversity of systems, recent research efforts are oriented to develop ITS to be applied in online education to monitor, track, record behaviors, and to perform formative assessment and feedback loop to students to foster a professional and reflective approach (Paviotti, Rossi & Zarka, 2012).

One of the most important characteristics of e-learning systems is that of being personalized, in order to fit the needs of a variety of students with different backgrounds and skills (Paviotti, Rossi & Zarka, 2012). Previous researches such as (Paviotti, Rossi & Zarka, 2012) proposed to consider aspects such as: learning style of the students, “personal predispositions” (memory, understanding, and content associations), psychological aspects, and affective states. The last two ones are focused on the types of emotions involved in the learning process.

Almost all the past researches propose a basic architecture for a tutoring system, which consists of the following elements: domain model, instructor model, learner model, expert model, and user interface. In those proposals, for the learner model there is not a complete user profile including all the human characteristics that are involved in the learning process. Several past works agreed that the user interface module is an important element that adjusts the learning environment to the user necessities. Even though this agreement, there is not a precise description about how they adapt the learning interface to the user characteristics.

In this paper we present a proposal to consider an integral user profile that includes the following user characteristics: cognitive, experience, psychological, demographic, sensory, affective, motivation, and physic. This proposal contributes to the orchestration of an adaptive intelligent tutoring system.

This paper is organized as follows. Section 2 describes some of the more relevant problems in the context of tutoring systems, and also presents the major trends. Section 3 exposes some related works. Sections 4 and 5 present our proposal for orchestrating an adaptive intelligent tutoring system. Finally, sections 6 presents the conclusions and future work.

2. Main problems, challenges and trends in the context of tutoring systems

Until today several systems have been implemented having significant results. Previous research reveals that tutoring system implementations commonly have been oriented on one type of tutoring system; there are not much evidences of implementations combining ITS, CAI, and AITS. In order to take advantage from them and to avoid their disappointments, we analyzed the main problems that are present in this context.

2.1. Expensive research for building tutoring systems

The research phase is often expensive; it requires the cooperation and input of subject matter experts, the cooperation and support of individuals across both organizations and organizational levels (Murray, 1999). A high portion of that cost is a result of content component building (Nkambou, Mizoguchi & Bourdeau, 2010), not only for the work of creating learning material, but also for the multidisciplinary required for that building. The time spent for developing the ITS is another expensive factor due to a big amount of human resources required for the system construction.

2.2. Limitations of the pedagogy of immediate feedback

The pedagogy of tutoring system currently in use is criticized; some aspects such as the immediate feedback and hint sequences that are built in to make the system "intelligent" present limitations. This pedagogy is criticized for its failure to develop deep learning in students. In some systems, when students are given control over the ability to receive hints, the learning response created is negative. “If students fail to reflect on the tutoring system's feedback or hints, and instead increase guessing until positive feedback is garnered, the student is, in effect, learning to do the right thing for the wrong reasons” (Koedinger & Aleven, 2007). In general terms, most of the tutoring systems are unable to detect shallow learning and therefore, the learning for some users is not optimal.

2.3. Lack of intrinsic motivation

Intelligent tutoring systems have been criticized for being too "instructivist" and removing intrinsic motivation, social learning contexts, and context realism from learning (Jonassen & Reeves, 1996). These systems commonly fail in using attractive and persuasive scenarios to take students to appropriate the domain language. In such situations, if the student is not learning the domain language it becomes more difficult to gain a deeper understanding, to work collaboratively in groups, and to transfer the domain language.

2.4. Lack of focus in learning content

Several systems have intended to be effective and useful, but they lead in improving the usability of the system, for example, some cognitive tools (e.g. simulations) can have the effect that learner learns the tool and not something that he can transfer (Ong & Ramachandran, 2003). This is well known as the *video game effect*, that is, learner learns to operate the system and their logic, but the system does not support the learnability of educational contents.

2.5. Lack of evaluation standards

There are various evaluation techniques presented in the literature, such as proof of correctness, additive experimental design, diagnosis accuracy, feedback/instruction quality, sensitive analysis, expert inspection, pilot testing, formative evaluations, and summative evaluations (Iqbal, Oppermann, Patel & Kinshuk, 1999; Siemer & Angelides, 1998; Mark & Greer, 1993). Even though the usefulness of these evaluation techniques, there are no guiding principles for the selection of an appropriate evaluation method to be used in a particular context (Iqbal, Oppermann, Patel & Kinshuk, 1999; Siemer & Angelides, 1998).

For instance, there are not precise recommendations for when to use each technique, that is, if it is better to apply them during the design phase, during the implementation phase, or after the completion of a tutoring system (Mark & Greer, 1993). In general, the great challenge introduced by the lack of evaluation standards resulted in neglecting the evaluation stage in several existing ITS' (Iqbal, Oppermann, Patel & Kinshuk, 1999; Siemer & Angelides, 1998; Mark & Greer, 1993).

2.6. The necessity of inclusion of Dialogue

This capacity aims with attempting to simulate natural conversations (Graessner, Kurt VanLehn, Jordan & Harter, 2001). This is based on the fact that human tutors have the ability to understand a person's tone and inflection within a dialogue and interpret this to provide continual feedback through an ongoing dialogue, including being able to understand tone, inflection, body language, and facial expressions and then to respond to these (Graesser, Chipman, Haynes &Olney, 2005).

2.7. The necessity of inclusion of Affective issues

This concerns with the possibility of interpreting the affective process of an individual; that is, being able to interpret and adapt to the different emotional states of the learner (D'Mello & Graessner, 2012; Sarrafzadeh, Alexander, Dadgostar, Fan & Bigdeli, 2008). This is based on the idea that affective processes that learners go through also play an important role (D'Mello, Olney, Williams & Hays, 2012). It is necessary to read an individual's expressions and other signs of affect in an attempt to find and tutor to the optimal affective state for learning.

3. Related works

We pretend to integrate the usability approach in the tutoring system design. Based on this, in this section we present some related works in two main areas: adaptive user interface design, and adaptive tutoring systems.

Several efforts have been made in order to support the design of adaptive user interfaces. Two of the most relevant proposals are described here. In (Weinschenk, 2011), a set of 100 affirmations are presented, which describe the way of how humans perceive, read, put attention, memorize, and think, what thinks motivate them, how decide, how socially they act, errors committed, etc. Also, an explanation is provided about the impact these aspects have over the user interface design. In addition, a set of recommendations is presented about what to do and what to avoid for user interface design.

In the other hand, in (Johnson, 2010), an explanation is presented about the sensory and cognitive limitations humans have, and how these limitations impact the user interface design.

In (Schiaffino, Garcia & Amandi, 2008) an intelligent agent that provides personalized assistance to e-learning students is presented. This agent observes a student's behavior while he/she is taking online courses and automatically builds the student's profile. This profile comprises the student's *learning style* and information about the student's performance, such as *exercises done*, *topics studied*, and *exam results*. The student's learning style is automatically detected from the student's actions in an e-learning system using Bayesian networks. Based on this, the agent proactively assists the student by suggesting him/her personalized courses of action that will help him/her during the learning process.

Phobun & Vicheanpanya (2010) presented a proposal for combining ITS and Adaptive Hypermedia systems (AH) into an Adaptive Intelligent Tutoring System (AITS) for e-learning systems. This approach pretends to take advantages from ITSs and the capabilities of AHs. In this case, it is considered that an AH is better suited for the instruction of concepts whereas ITS generally assists in the use of these concepts to solve problems. This proposal considers two main elements of the user profile: *current knowledge* and *learning style.*

Sansoni & Giannandrea (2012) presented a proposal for the user profile in a tutoring system. They suggested that it contains pieces of information about the basic characteristics and habits of the user. Discovering these individual peculiarities is vital to provide users with a personalized service. The user profile stores learning activities and interaction history. It is created through storing both static information (as the previous course followed by the student), and dynamic information (as the learning activities that the student is doing).

Analyzing works such as (Schiaffino, Garcia & Amandi, 2008), (Sansoni & Giannandrea, 2012) and (Phobun & Vicheanpanya, 2010) we have found that there is a misconnection between leaning focus developments and user interface design approaches. Even though tutoring systems are software systems, commonly learning-oriented researches only consider aspects from the learning theory, but not consider user interface design principles.

4. Orchestrating the Adaptive Intelligent Tutoring System

ITSs incorporate a built-in expert system. Based on this idea we propose to consider various intelligent modules. In order to monitor the performance of the learner and to personalize instruction on the basis of adaptation to learners' learning style, current knowledge level, and appropriate teaching strategies (Phobun & Vicheanpanya, 2010), in this section we describe how we are orchestrating our AITS.

For orchestrating the user profile we use a Human-Computer Interaction (HCI) point of view due to we have previous works in this context (Mejía, Juárez-Ramírez, Inzunza, & Valenzuela, 2012; Mejía, Juárez-Ramírez, Inzunza, & Valenzuela, 2013; Mejía & Juárez-Ramírez, 2013); we believe that HCI makes a better consideration of the user analysis for system design. Based on this, we propose in consider an integral user profile that includes user aspects such as: cognitive, experience, psychological, demographic, sensory, affective, motivation, and physic. Considering this integral user profile will help us to have a more useful and usable tutoring system.

4.1. Orchestrating the AITS modules

IEEE Std. 1471-2000 (Hilliard, 2000) defines software architecture as *the fundamental organization of a system; architecture is integrated for components, relations between them and the context where components will be implemented, and the principles that conduct the architecture design and evolution*. The traditional ITS model contains four components (Freeman, 2000): the *domain* model, the *learner* model, the *teaching (instructional)* model, and a *learning environment* (*user interface*). We are considering other related models for integrating the

AITS architecture (Phobun & Vicheanpanya, 2010): *expert model*, *tutor model*. Figure 1 shows our proposed architecture.

ITS projects can vary tremendously according to the relative level of intelligence of the components (Freeman, 2000). Each model can involve a level of intelligence in order to deals with its work inside the whole system. Based on this, we focus this description to where artificial intelligence is needed in each model and modules. Our architecture adapted from previous proposals.

Domain model. Represents the subject matter –expertise- and provides the AITS with knowledge of what it's teaching (Ong & Ramachandran, 2003). In the best scenario, it should be able to solve the problems the tutoring module submits to the students (Freeman, 2000). This module is very related with the expert model. *Artificial intelligence* would be needed for: (1) Generating solutions to complex problems, (2) generating novel problems, so that students can always have new problems to practice on.

Learner model. This model represents the student's knowledge, skills, and other attributes that affect how the student should be taught (Ong & Ramachandran, 2003). This model lets the AITS know who it's teaching. It reflects what the machine can infer about the student's cognitive state (Freeman, 2000). *Artificial intelligence* would be needed for: (1) evaluating each learner's performance to determine his or her knowledge, perceptual abilities, and reasoning skills (Ong & Ramachandran, 2003), (2) determining appropriate and inappropriate actions carried out by the learner, (3) predicting what the learner does or doesn't understand based on sequences of actions and states associated with concepts to learn.

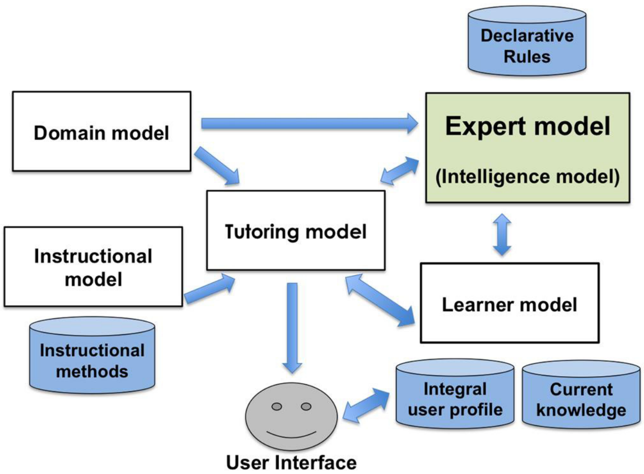

Fig. 1. Main architecture of the AITS

Instructional model. This model encodes instructional methods that are appropriate for the target domain and the learner and enables the AITS to know how to teach (Ong & Ramachandran, 2003). It contains knowledge for making decisions about instructional tactics. It relies on the information for diagnostic processes of the learner model for making decisions about what, when and how to present information to a leaner. *Artificial intelligence* would be needed for: (1) cataloguing the expertise level (knowledge possession) of learners, (2) determining the level of complexity of the learning materials to be presented to the learner based on hos/her expertise level, (3) deciding when to increase the complexity level of learning material for a learner, (4) choosing topics and examples that are relevant for the learner.

Tutor model. This model controls the interaction with the learner, based on its teaching knowledge and comparisons between the student model and the domain knowledge (Freeman, 2000). Based on its knowledge of a person's skill strengths and weaknesses, participant expertise levels, and student learning styles, this model selects the most appropriate instructional intervention. Also provides feedback, explanations, and coaching as the participant performs the simulated procedures. It might even pose questions, using Socratic teaching methods, to encourage students to reflect upon their actions and reasoning. *Artificial intelligence* would be needed for: (1) making decisions about what learning material and how to present this information to the leaner.

Expert model. This module is a representation of a domain expert's subject matter knowledge (declarative knowledge) and problem-solving ability (procedural knowledge) (Ong & Ramachandran, 2003). It combines and applies rules to solve the problems. Also, it assesses each learner's understanding by comparing the software's reasoning with theirs, and demonstrates the software's solutions to the participant's (Ong & Ramachandran, 2003). *Artificial intelligence* would be needed for: (1) inferring the learner's needs to practice and learn at their own pace, (2) making decisions about what, when and how to present information to a leaner.

User interface model: This model is important as a communication medium and learning environment that can support learning tasks. It can also act as an external representation of the expert model and instructional model. *Artificial intelligence* would be needed for: (1) inferring motivation and affective conditions to present to the learner based on their actions and achieves, (2) adapting the user interface characteristics to the user profile.

4.2. A proposal for an integral user profile

In the learning process there are two main parts, the student and the teacher. From the student point of view, there four characteristics to consider: *prior knowledge*, *learning style*, *intelligence*, and *motivation* (Huitt, 2003). Also, in de student side, during the learning process there are three main elements to consider: *content overlap*, *involvement*, and *success*. As a result of the learning process the student has achievement *–learning*. As the student is the main part of the learning process, in this section we describe a user-centered perspective, which helps giving to the tutorial system a software system orientation whose main objective is the student learning.

From the HCI point of view, user interface designers have considered simplicity and easy for learning (Biswas 2012; Biswas & Robinson, 2013). Other aspects of the user should be considered. User modeling has as objective the representation of preferences, abilities and knowledge possessed by the user (Biswas & Robinson, 2013; Tatjana & Alexander, 1997) in order to achieve usable and useful interfaces. The term "usable" in concerned with usability, while the term "useful" is concerned with usefulness. Relating these concepts, we can say that usefulness involves utility and usability. Utility concerns whether the system design provides the features user needs. Usability concerns with how easy and pleasant these features are to use.

Usability is often associated with the functionalities of a system. In the context of tutoring systems, those functionalities are related with presenting learning materials to the students, tests application, feedback to the students, and so on. From this point of view, "useful" concerns with *understanding what the learners who will be using the software want to achieve —what their goals are and how they go about achieving them*; *in this case, learning new knowledge and master new abilities in an easy way*. This implies getting a better understanding of the learners and what they want to achieve, also understanding their motivations —what encourage them, what they like and don't like about what they do, and more.

Based on these ideas, for user modeling, it is necessary to consider the majority of human characteristics involved in the interaction with a machine or a software system. A human factor is a user characteristic that has relevance in the interaction between the user and the machine, a system or a product (Zudilova-Seinstra, 2007). Table 1 shows a set of factors to consider for the user modeling. These groups of factors have been integrated from the proposals made in (Stuart, Card & Newell, 1983; Cañas, Gámez & Salmerón, 2001; Quiroga, Crosby & Iding, 2004; Zudilova-Seinstra, 2007; Johnson, 2010; Weinschenk, 2011).

We are planning to consider the majority of these aspects for our AITS implementation. A first proposal for implementing the "adaption" in our AITS is taking into account the following aspects: cognitive (learning style), motivation (attitudes), affective (emotions), experience (technological abilities), demographic (scholarly, gender), physic (motion abilities), sensory (all sense), psychological (motivation, self-confidence).

Table 1. Factors for the integral user profile.

Factor group	Description	Examples of factors/attributes
Cognitive	Concerns with how humans process information; it is related with the mind and its processes.	Perception, memory, attention, concentration, decision making, learning capacity, learning style.
Motivation	Motivation engages the learner to use the system; it influences directly how the learner perceives and interprets the system.	Attitudes, necessities, expectances.
Affective	Concerns with the affective processes of an individual; that is, expressing the different emotional states of the learner.	Emotions: curiosity, satisfaction, awe; hopefulness; confusion, disappointment; frustration, discard, misconception (Shen, Wang & Shen, 2009;Kort, Reilly & Picard, 2001); Hao, 2003)
Experience	Concerns with the context of the learner, and is related with the learner previous experience with the system's domain, and using alike systems.	Technological abilities, knowledge over the system.
Demographic	Helps to put learner into a context in personal aspects; does t have a direct impact on the user interface, but it defines important aspects for learning.	Age, gender, scholarly, culture.
Physic (motion)	Aspects concern with human motion system, muscles and physical movements.	Motion abilities, movement control, and coordination.
Sensory	Concerns with such aspects related with the five senses of humans, which contribute to communication process.	Visual (eye-gate), auditory (ear-gate), hand-on (touch and physical movement). (Shams & Seitz, 2008)
Psychological	Concerns with the function of the human body, the mechanics, bioelectrical, and biochemical.	Motivation, self-efficacy, self-esteem, self-confidence. (Rahman, Yasin, Amir & Embi, 2011).

4.3. Summarizing aspects for building the adaptive intelligent tutoring system

Considering the nature and functions of each model from the tutoring system architecture and the description of the user factors, we established a connection between them as we can see in Table 2. In advance, the learner model would take into account all the user characteristics. The same case is for the tutor and user interface models.

Table 2. Determining the adaption – mapping the tutoring system models with the user characteristics

Factor group	**Domain model**	**Learner model**	**Instructional model**	**Tutor model**	**Expert model**	**User interface model**
Cognitive	√	√	√	√	√	√
Motivation		√	√	√	√	√
Affective		√	√	√	√	√
Experience	√	√	√	√	√	√
Demographic		√	√	√	√	√
Physic (motion)		√		√		√

Sensory	√	√	√	√	√	√
Psychological	√	√	√	√	√	√

The adaption is focused mainly in two components, the learning material and the user interface. For the learning materials, first we are proposing to present student learning materials respecting the complexity of contents depending on the previous knowledge and current student performance. Aspects such as demographic and experience are related with this factor. In the case of user interface, aspects such as motivation, affective, psychological, sensory and physic will contribute to adapt the user interface in terms of: visual effects, auditory effects, and animation.

4.4. Defining the complexity of learning materials

In order to determine the complexity level of the learning materials to be presented to the learner, by the moment, we are considering the following factors: *reading times*, *reading time*, *number of exercises done*, *test score*, and *test time*. We have proposed these factors derived from a survey applied to undergraduate students. Based on their experience, they considered that these factors could determine the complexity level for the learning materials. The *reading times* factor represents the number of times that a learning material (of a specific theme) has been read. The *reading time* means the time spent for reading this material. The *number of exercises done* means how many exercises the learned have done for a specific theme and learning material. The *test time* means the time spent in answering a test. The *test score* represents a score in a specific test for a learning material.

Combining these factors we can determine the level of complexity of the learning material (see Figure 2). We are considering three complexity levels: basic, intermediate, and advanced.

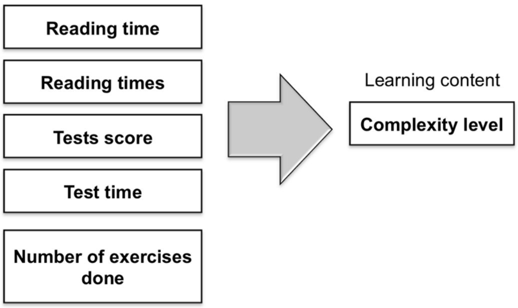

Fig. 2. Factors to define the complexity level of learning materials

It is important to emphasize that the number of factors would not be limited to this set; another variables can be considered taking into account the user characteristics contained in the integral user profile.

4.5. Learning material generation

As a first proposal, we are planning to generate learning materials considering three complexity levels and three learning styles (see Figure 3). We have the following combinations of learning materials: Basic level – Visual style, Basic level – Auditory style, Basic level – Kinesthetic style; Intermediate level – Visual style, Intermediate level – Auditory style, Intermediate level – Kinesthetic style; Advanced level – Visual style, Advanced level – Auditory style, Advanced level – Kinesthetic style.

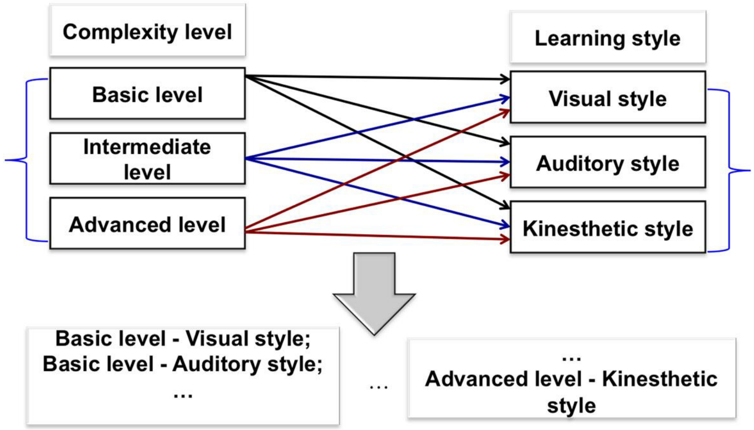

Fig. 3. Generating learning materials

By the moment, this classification helps us to present a complexity level to each student based on his/her performance.

We have implemented a set of learning materials for teaching object oriented programming. We implemented two formats for learning materials: textual explanations, and videos. We have probed the usefulness of these materials having significant opinions from students about the capacities of these materials for teaching this topic.

5. Orchestrating the intelligence of the Tutor Model

Considering that some factors have different ranges of values, for instance, *test score*; a fuzzy method has been selected for modeling and implementing the intelligence for the tutoring module. We propose to use a Mamdani method. This system has as numeric values as input; values are processed and after that a fuzzy output is generated. Bellow we describe the factors and data to be the input for the Mamdani algorithm.

In order to detect the learning style, we have considered a tool that consists in a questionnaire based on specific questions that emphasize aspects of the visual, auditory and kinesthetic styles. This tool is included in our prototype called TIPOO (in Spanish "Tutorial Inteligente para la Enseñanza de la Programación Orientada a Objetos"). The results from this tool will be stored in the learner profile inside TIPOO. Also, we have considered a timer module to measure the time spent in reading, in this way, the time spent in reading a topic will be stored in the learner profile. We have designed a test tool, which automatically calculates the score for each test. We propose the following score intervals: *low* (0-59), *acceptable* (60-79), and *excellent* (80-100). In addition, we have considered a timer for measuring the time spent in answering a test. For the test time we have define ranges of values, having these intervals: *low*, *acceptable*, and *excellent*. For reading time we also have ranges of values, but they are mapped to the following intervals: *low*, *intermediate*, and *fast*.

In Table 3 we present a partial set of fuzzy system rules for determining the complexity level (see the fourth column), in this case we only show the rules for the kinesthetic learning style. In the same way we have proposed rules for visual and auditory learning styles, but they are not showed here.

Table 3. Fuzzy system rules – Kinesthetic learning style

Test score	Reading time	Test time	Complexity level	Learning style
Low	Low	Low	Basic	Kinesthetic
Low	Low	Acceptable	Basic	Kinesthetic
Low	Low	Excellent	Basic	Kinesthetic
Low	Intermediate	Low	Basic	Kinesthetic
Low	Intermediate	Acceptable	Basic	Kinesthetic
Low	Intermediate	Excellent	Basic	Kinesthetic
Low	Fast	Low	Basic	Kinesthetic
Low	Fast	Acceptable	Basic	Kinesthetic
Low	Fast	Excellent	Basic	Kinesthetic
Acceptable	Low	Low	Intermediate	Kinesthetic
Acceptable	Low	Acceptable	Intermediate	Kinesthetic
Acceptable	Low	Excellent	Intermediate	Kinesthetic
Acceptable	Intermediate	Low	Intermediate	Kinesthetic
Acceptable	Intermediate	Acceptable	Intermediate	Kinesthetic
Acceptable	Intermediate	Excellent	Intermediate	Kinesthetic
Acceptable	Fast	Low	Intermediate	Kinesthetic
Acceptable	Fast	Acceptable	Intermediate	Kinesthetic
Acceptable	Fast	Excellent	Intermediate	Kinesthetic
Excellent	Low	Low	Advanced	Kinesthetic
Excellent	Low	Acceptable	Advanced	Kinesthetic
Excellent	Low	Excellent	Advanced	Kinesthetic
Excellent	Intermediate	Low	Advanced	Kinesthetic
Excellent	Intermediate	Acceptable	Advanced	Kinesthetic
Excellent	Intermediate	Excellent	Advanced	Kinesthetic
Excellent	Fast	Low	Advanced	Kinesthetic
Excellent	Fast	Acceptable	Advanced	Kinesthetic
Excellent	Fast	Excellent	Advanced	Kinesthetic

Table 3 represents only a first proposal to manage the complexity level of learning materials and the learning style, but actually the user profile and the learning process involve a broad set of factors, some of them can have precise values, but others don't have exact values and states. Based on this, we would have to decide what type of uncertainty techniques we need to use for managing that level of knowledge about the user profile and the learning progress. In (Kasabov, 1996; Konar, 2000; Netnevitsky, 2011) uncertainty reasoning principles and techniques are presented that should be considered in order to select the appropriate techniques.

In (Netnevitsky, 2011) is stated that *uncertainty* is the lack of exact knowledge that would enable us to reach a perfectly reliable conclusion. In this context, *approximate reasoning* is a process of interpretation of knowledge in a presence of uncertainty in a form of vague and contradictory knowledge, incomplete past data, uncertain new facts, not clear goals, etc. (Kasabov, 1996). In (Konar, 2000) is stated that in the presence of forms of inexactness of data and knowledge, the following methodologies are suggested: (1) *probabilistic techniques*, (2) *certainty factor-based reasoning*, and (3) *fuzzy techniques*. As is stated in (Kasabov, 1996), different representation schemes influence the type of approximate reasoning techniques that can be used. Examples of representation schemes are: simple fuzzy rules, weighted production rules, and generalized fuzzy production rules.

6. Conclusions and future work

In this paper we have presented a general view of how to orchestrate an adaptive intelligent tutoring system, respecting the architecture of traditional tutoring systems, but emphasizing the inclusion of an integral user profile, which considers the majority of the human user characteristics: cognitive, emotion, affective, sensory, demographic, experience, physic, and psychological. This integral user profile facilitates the implementation of the intelligent modules and the user interface in order to have a more adaptable tutoring system.

We have introduced a new perspective for the user profile, which includes all the user characteristics that take part in the learning process. This perspective differs from previous research because they don't precise a specific set of characteristics and attributes of the user.

Even though by the moment we developed a prototype, we are working on the construction of a complete system, implementing the intelligence for each model as intelligent components in the AITS architecture.

Our future work is divided in different topics, but they are strong related as we can see in the following description:

Tutor-ability model. Taking advantage from our expertise in measuring learnability in software systems and also in videogame systems, we are defining a set of factors and properties for integrating a tutor-ability model. In educational contexts, students like to feel that they are making progress; they like to feel that they are learning and mastering new knowledge and skills. Based on this, in terms of teaching, we can define tutor-ability as *the capacity of an ITS for facilitating learning and mastering new knowledge and skills*. Towards integrating a set of attributes for defining tutor-ability, we have adopted some factors and properties from the playability model exposed in (González, Padilla & Gutiérrez, 2009). We considered that the factors presented by the playability model proposal are very related with the type of tutoring systems we are looking for because it is a good challenge to adapt learning materials to games features, such as immersion, motivation, emotion, and so on.

Tutor-ability metrics. Taking advantage from our expertise in software metrics, we are integrating a set of metrics to assess the capacity of ITS to assist learning process and students progress.

Natural language processing. In order to attend the necessity of integrating dialogue and feedback capacities, we are considering including the capacity of using text-based questions from the learner to the system. This capacity will be implemented adopting our past proposal (Huertas, Juarez-Ramirez, Gomez-Ruelas & Plata, 2011; Huertas & Juarez-Ramirez, 2012) for the treatment of structured texts, but extending this capacity to non-structured texts in order to make more flexible the interaction between the learner and the system. In addition, following this approach we are planning to integrate speech-based dialogue.

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