Integrated Approach for the Detection of Learning Styles & Affective States

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Abstract: Detecting the needs of the learner is a challenging task for systems addressing issues related to either adaptivity or personalization. In this paper we present a student-driven learning and assessment tool along with a tool for detecting/calculating learning styles and affective states. The learning and assessment tool enables learning, while the detection/calculation tool detects learning styles and affective states from the behavior of learners. The resulting behavior is then reflected in the database. This method does not require learners to fill out a lengthy questionnaire. Also, there is no need to monitor observational cues, such as gesture, posture, conversation etc. of the learner; the detection/calculation tool automatically identifies learning styles and affective states.

Introduction

Modeling the features of the learner is pertinent for systems providing methods to deal with either adaptivity or personalization issues (Graf et al. 2006). For that reason, the user model is a main component of any adaptive system. The user model presents information about an individual user, allowing adaptive systems to use this information to provide adaptation effects (Brusilovsky 2007). When building an adaptive system, adaptation is usually based on a user's knowledge, goals, and preferences. Adapting to a user's personality traits or his/her affective states, such as motivation and emotion, are rarely considered (Dautenhahn 2002).

Graf and Kinshuk (2006) emphasized the fact that the needs of the learners must first be known before adaptivity can be provided. Bruisilovsky (1996) has mentioned two different approaches for obtaining information about a learner's needs: the collaborative and the automatic student modeling approach. In the collaborative modeling approach, learners provide explicit information about themselves by filling out a questionnaire, whereas in the automatic modeling approach, the system monitors the actions and behavior of learners and infer their needs automatically while they are learning/working within the system.

In systems that provide adaptation based on the affective state of the learner, observational cues such as gesture, posture, conversation, etc. are used. According to Cocea (2006), it is very difficult for adaptive systems to process these kinds of observational cues. That is why most research attention is shifting towards systems that automatically process motivation/emotion cues as a means to assess affective states.

With traditional teaching methods and high student/teacher ratios, a teacher faces great obstacles in the classroom. Traditionally, teachers deliver the content and students learn it. With this methodology, teachers are usually not able to respond to the individual needs of students. Furthermore, due to the large numbers of students in a classroom, teachers are not able to focus on each individual student. For grading purposes they normally conduct an exam at the end of the course. However, despite the high number of students in a classroom, experienced teachers usually observe, recognize and address the learning style and affective state of the learners. The skilled teacher takes suitable action to positively impact learning. But the question is what these experienced teachers "see" and how they arrive at a course of action and whether this action leads the learner to a productive path.

Learner's learning is not only governed by factors like instructor's teaching style, learner's native ability and prior preparation but also by the compatibility of his/her learning style and his/her affective state. The learning styles and affective states can be affected by a learner's educational experience. For example a learner takes a well taught course that provides guided practice in intuitive skills while the learner has a strong preference for sensing. This will result in gradual increase in the comfort level or confidence level with abstract conceptualization and consequently a gradual decrease of his/her preference for sensing, whereas the learner's native ability, skills and knowledge influence his/her performance.

We believe that accurately identifying learning styles and affective states is a critical step in understanding how to improve the learning process. We also believe that computers will soon be capable of recognizing human behavior and producing accurate assessments regarding learning styles and affective states.

Previous Research and Our Perspective

Previous Research

Related work deals with the identification of learning styles in adaptive systems, such as ILASH (Peña 2002), MASPLANG (Marzo et al 2003), and CS383 (Carver 1999). These systems use collaborative student modeling or a self reported informational approach for detection of learning styles. This approach has at least two potential downfalls (Shute 2007).

1. First, learners can provide inaccurate data due to a lack of knowledge about their own characteristics either accidentally or purposely, due to privacy concerns.
2. Second, during the online learning process, completing the questionnaire can be time consuming, which might frustrate learners and lead them to provide invalid data in order to arrive at the content more quickly.

Only a few other systems adopted automatic modeling approaches such as Arthur (Gilbert 1999), which is a Web-based instruction system. In an automatic student modeling approach there is no additional effort necessary on the part of learners in order to obtain information about their learning styles. Learners simply interact with the system while learning and the system infers their learning styles and accommodates their needs. The information obtained in this way is free from uncertainty. DELES (Graf 2007) detects learning styles from the learners' different patterns of behavior, such as the number of visits in a forum, the number of times they participate in a chat, the number of postings in a forum and the number of visits, and the time a learner takes to deal with exercises.

Related work regarding identification of affective states comes either from observation cues, such as Itspoke(D'Mello 2006) or Mota(Kapoor et al 2004) or through interaction with the system, such as Vfts(Roll 2005).The affective state detection through observational cues has one drawback, that is, once learners become aware that their learning activities are being monitored, there is a chance that they will become nervous or anxious or even depressed before beginning their regular learning activity and will perhaps continue to maintain this emotional state throughout the learning experience.

Our Perspective

We propose a simple architecture that is easy for learners to use, for detecting learning styles and affective states. Our approach integrates information about learning styles and affective states, such as motivation/emotions, in order to enable educational systems to provide personalized and more efficient adaptation based on the features shown in Figure 1.

Our approach aims at inferring the learning styles and affective states (i.e., motivational/emotional states) from the behavior of the learners instead of using a questionnaire to ask the learners about their preferences for learning styles and observational cues for affective states. The proposed learning and assessment tool/framework tracks the learners' knowledge progress, provides an assessment, and supports the learner by offering hints, help, and feedback. The proposed learning styles and affective states tool not only calculates the learning style from patterns of behavior but it also predicts certain components of the affective state i.e. motivational/emotional state of each individual user while interacting with the system.

In our approach learners will be informed/ provided awareness before entering a regular learning and assessment session that the data, which will be generated by interacting with learning and assessment tool, will be used by the calculation component to profile the learners 'learning styles and affective states; in addition we also provide assurances that the use of data will be in compliance with European Union data protection legislation (Rößling et al. 2008). After getting awareness and assurances, conscientious learners will not become nervous or anxious or even depressed to use the learning and assessment tool and will be pleased that they are not formally assessed.

We also propose an indirect approach to motivate/ encourage students to use the student driven learning and assessment tool by introducing classroom quizzes, as classroom quizzes have a great role in motivating students to learn (Brusilovsky 2005). This can be accomplished by introducing 8 to 10 classroom quizzes per semester/course. During a quiz the student will be asked to answer 10 questions within 10 minutes related to topics discussed during the most recent last lecture.

This approach not only motivates, but engages the student to use student driven learning and assessment tools for learning. Thus the students who worked with the learning and assessment tools after each lecture will be able to answer most of the questions in the classroom. These approaches enable the categorization into a database of behavioral patterns, calculation of learning styles, and prediction of affective states for a majority of students

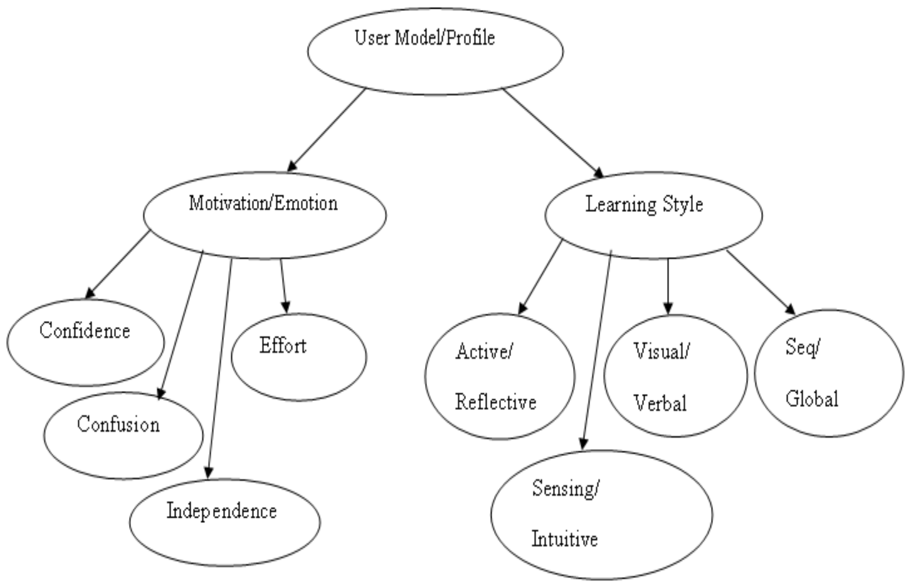

Figure 1: User Model/Profile

Learning and Assessment Tools Architecture

In this section we present the student-driven learning and assessment tool, in which an initial learning activity takes place followed by an assessment. The architecture is shown in Figure 2

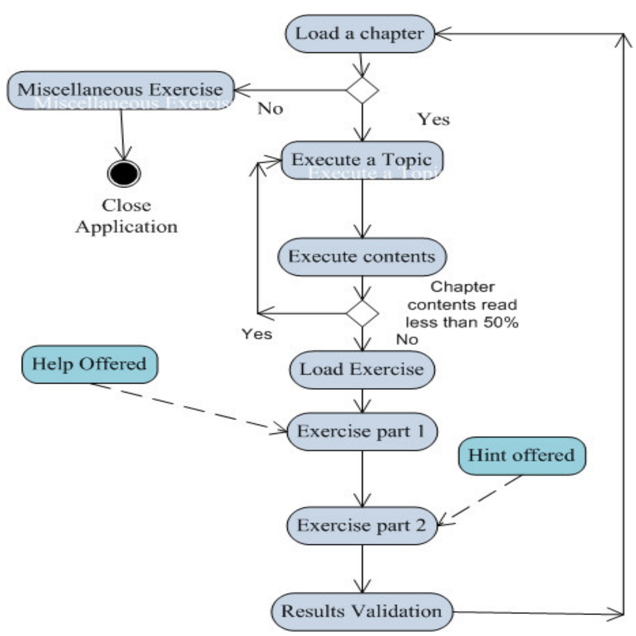

Figure 2: Learning and Assessment

The learning and assessment tool first offers the learner a "learning" or lesson for learning. The learning format is text with graphics/diagrams, as applicable. The learning interface consists of two main windows-the outline frame and the content presentation frame. In the outline frame chapters are presented. Learner will have to select one of the chapters presented. Each chapter consists of a number of topics. Upon selecting/clicking a topic, its contents are presented in a content presentation frame. This action of selection/clicking is recorded by the system i.e. it means that the learner has visited that contents. The learner has the option to select the next topic randomly instead of following the sequential order. When the learner finishes reading the chapter, the system will check whether the learner has visited 50 percent of the topics of the chapter. System will get this acquired information from the number of visited learning topics. Moreover this event is not timed but judged on visiting topics. If the learner has visited at least 50 percent of the topics, the system will ask the learner if he/she wishes to move ahead to the next exercise or complete the reading of the existing contents. If the learner selects the option to go ahead, an exercise is offered. Otherwise, the system switches back to reading the content section again. If the learner has not read 50 percent of the contents of the chapter/module, the system will recommend the learner, to continue reading the remaining content. The proposed tool/framework supports and motivates the learners' during the assessment process in the form of offering hints and help. Each assessment exercise consists of two parts. The first part comprises multiple choice questions. At this point, a help window is available. The learner can use the help window to reread the applicable topic. Here the learner will be able to avail the help facility a fixed number of times i.e. 3 times while attempting the first part of exercise. After finishing the first part, the second part of the exercise requires filling in the blanks. In this second part, a relevant hint is available. If learners do not understand the particular question, they can look for a hint; often a more precise and simple explanation. Here again the learner will be able to avail the hint facility a fixed number of times. At the end of each exercise, results are validated. If incorrect, the correct solutions are described. The system continues in this manner for each chapter. The help screen and the hints are provided in order to motivate the learner and prevent giving up or dropping out. The restriction of offering the help and hint window/facility only a fixed number of times has been introduced in order to avoid "help and hint abuse" i.e. those learners who quickly and repeatedly ask for help and hint instead of attempting the exercise on his or her own. When the learner has finished all the learning and assessment modules/lessons, a final miscellaneous exercise is offered. These final questions are based on all of the prior learning modules/lessons. No help or hint is offered, in order to rate improvement.

Learning Style Models

There are several theories pertaining to learning styles, such as Felder-Silverman learning style model (FSLSM) (Felder 1988), Honey and Mumford (Honey and Mumford 1982), and Kolb's Learning style model (Kolb 1984), etc. While other learning style models classify learners in few groups, the Felder-Silverman learning style model categorizes the learning styles of learners based on four dimensions (active/reflective, sensing/intuitive, visual/verbal and sequential/global), so that each learner has a preference for each of these four dimensions.

That is why FSLSM, shown in Fig. 3, is most appropriate for educational systems; and our work is based on it.

Dimensions	Definitions
Verbal	Require written or spoken
Visual	Remember what they have seen
Sequential	Learn in linear steps
Global	Holistic or learn in large leaps
Active	Learn by trying things
Reflective	Learn by thinking things out
Sensing	Learn concrete material and tend to be practical
Intuitive learners	Learn concepts

Figure. 3. Felder-Silverman learning style model

Felder and Silverman formulated a learning style assessment instrument, consisting of 44 questions known as Index of Learning Styles (ILS) questionnaire (Felder & Soloman, 1997). Numerous research studies have documented the reliability and validity of this instrument (Felder 2005).

Affective States in E-learning

In most of the e-Learning systems, including adaptive systems, attention is either towards knowledge acquisition or cognitive processing. When building a system, affective states such as motivation and emotion, are considered only in terms of how the content is structured and presented. To make learning efficient and to deliver personalized content, adaptive systems are based on models of a user's goals, knowledge, and preferences. Thus, a user model that integrates the cognitive processes and motivational states would lead to more efficient and personalized adaptation (Cocea 2007).Transforming a non-affect sensitive system into a system that is responsive to a user's affective states requires the modeling of a cycle known as the affective loop. The affective loop encompasses detection of a user's affective states, appropriate actions selection for decision making, and the synthesis of appropriate affective state by the system (D'Mello 2008).

According to Weimin (2007), affection influences the learning performance and decision making. This means that students who become caught in affective states such as anger or depression do not absorb information efficiently. From this, it can be inferred that a user's affective state has a major role in improving the effectiveness of e-learning.

Patterns of Behavior

Detecting learning styles and affective states occurs by detecting patterns that indicate a preference for a specific dimension and also for a specific affective state. We focused on commonly used features, such as content objects and exercises. The patterns of behavior considered for detecting learning styles and affective states are:

1. Time spent learning/reading each activity i.e. contents.
2. Time spent learning/reading contents containing graphics/diagram.
3. Time spent solving exercises.
4. Number of incorrect answers in each exercise related to graphics/diagrams.
5. Number of incorrect answers in each exercise.
6. Number of incorrect answers in final miscellaneous exercise.
7. Number of changes to the exercise answer.
8. Number of questions left unattended in each exercise per session.
9. Number of independent sessions of work with the system.
10. Number of solved exercises.
11. How many times the student has reviewed the topic/contents.
12. Attempted order to answer questions in exercise (sequential/ random).
13. Skipping pages/slide content sections.
14. Mouse clicking through the interface.
15. How often and how insistent the learner looks for help.
16. How often and how insistent the learner looks for hints.

These patterns of behavior are also called observable variables. Each of these patterns gives an indication related to a learning style dimension and an affective state.

Learning Styles from Patterns of Behavior

1. ***Active/Reflective Learners***

According to FSLSM, active learners prefer to process information actively by doing something with the learned material, such as discussing it, explaining it, or testing it. We can therefore assume that the following behavior provides us with hints about the learner's preference for an active learning style: Low number of sessions to complete the learning process, less time taken to complete the reading/learning content as compared with the time taken to solve the exercises, low number of times the learner looks for help, low number of times the learner looks for hints and does so less insistently, high number of performed exercises.

According to FSLSM, reflective learners prefer to think about and reflect on the learning material. Moreover they prefer to work alone. We can therefore assume that a situation that provides little or no opportunity to think about the information presented, reflective learners do not learn properly. Furthermore we can also assume that spending more time on learning/reading contents provides us with hints about the learner's preference for a reflective learning style.

*2. **Sensing/Intuitive Learners***

According to FSLSM, sensing learners like to learn facts and concrete learning material. Sensing learners also dislike challenges/complications and like to solve problems through well-established methods. Sensing learners usually work carefully and slowly. We can therefore assume that sensing behavior of learners can be predicted through: Number of times the student has reviewed the topic/contents, Number of times he or she changes the exercise answers, Time spent on solving the exercise.

According to FSLSM, intuitive learners welcome challenges and are bored by details. Intuitive learners tend to work faster. Furthermore, they like innovation and dislike repetition. We can therefore assume that a learner who does not revise his exam /assessment test tends to have an intuitive learning style. Moreover, high the number of solved exercises and low the time spent on solving each exercise also reveals the learner's aptitude for intuitive behavior.

*3. **Visual/Verbal Learners***

According to FSLSM, visual learners remember best what they see: demonstrations, films, diagram, and pictures; and create appropriate mental images of it. We can therefore assume that spending less time on learning/reading contents that contains graphics/diagrams and then performing well in exercises on questions related to such contents gives an indication of a learner's visual aptitude.

According to FSLSM, verbal learners prefer words either oral or written, as their method of learning. We can therefore assume that a great deal of time on learning/reading contents that contain graphics/diagrams and showing poor performance in exercise on questions related to those contents gives us an indication of his/her verbal learning aptitude. Conversely, performing well in exercises on questions related to the textual content further strengthens the indication of his/her verbal learning style.

*4. **Sequential/Global Learners***

According to FSLSM, sequential learners not only explore the course material sequentially, in detail but also follow linear reasoning processes when solving problems. We can therefore assume that not skipping pages/slide content sections can give a hint for a sequential learning style, indicating sequential behavior in exploring the course material. Moreover, the sequential selection/clicking order of questions in exercises also hint at a learner's aptitude for sequential behavior.

According to FSLSM, global learners are not interested in obtaining details of the contents being presented but instead, like to get an overview of the contents. Using this way of learning they get the big picture and build their own cognitive map of the contents. We can therefore assume that skipping pages/slide content sections can give a hint for a global learning style, indicating global behavior in exploring the course material. Moreover, the random selection/clicking order of questions in exercises also hint at a learner's aptitude for global behavior.

Affective States from Patterns of Behavior

(Qu, Wang and Johnson 2005) described several factors including confidence, confusion, and effort that influence learners' affective states, e.g., motivation. These factors have been said to be important following the background tutor studies. (Vicente and Pain 2002) described in their motivational model an independence that is relevant to the challenge and also relates to interpersonal motivational factors, such as cooperation, competition, and recognition.

The variables in our approach are: confidence, confusion, effort, and independence. These variables represent characteristics of the students that relate to the contents and exercises. Following the Qu model and Vicente motivational model, affective states predicted from the patterns of behavior are explained below.

*1. **Confidence***

According to Qu, Wang and Johnson model for pedagogical agents, the confidence of a learner in a learning environment is defined by the confidence of the learner in solving problems. We can therefore assume that the following behavior provides us with hints about the student's confidence distinguishing between high, normal, and low confidence i.e. High number of correct answers in each exercise, High number of solved exercises. A learner's confidence can also be inferred from mouse movement/clicking throughout the interface. This movement / clicking of the learner also confirm that the learner was paying attention to the task / exercise answers. If the task is performed quickly and is also performed well, it can be inferred that the learner was confident. If the learner performed a task quickly, it can also mean a lack of interest. But the combination of other pieces of evidence, such as that the learner was interested in performing the task and also he /she performed well, leads to the assumption that in such cases, quick performance is due to high confidence.

2. ***Confusion***

According to Qu, Wang and Johnson model for pedagogical agents a learner in highly confused state is most likely to be stuck or frustrated. We can therefore assume that the following behavior provides us with hints about the student's confusion i.e. High number of incorrect answers in each exercise, Low number of solved exercises. Also the state of confusion can be inferred from how many times the learner has asked for help or hint in solving the exercise. Moreover the number of questions left unattended in each exercise per session i.e. not completing the exercise and leaving the session abruptly, gives an indication of the learner's state of confusion.

3. ***Effort***

According to Qu, Wang and Johnson model for pedagogical agents, a learner's effort can be seen in the amount of time the learner spends on performing tasks. We can therefore assume that the following behavior provides us with information related to the learner's effort: The amount of time the learner spends on performing tasks, such as the total time taken reading the contents and solving exercises, predicts a learner's effort. Effort is a fundamental indicator of a learner's motivation. The exertion of effort is considered by human tutors as a positive parameter and they praise learners for extending effort even when they are not successful. (Schmitz and Skinner 1993) indicated that a lack of effort hinders cognitive accomplishments and the learners who have high ability and also they exert more effort have a capacity beliefs. The capacity beliefs promote subsequent control and are beliefs in a high capacity to exert high effort and ability.

4. ***Independence***

According to Vicente and Pain motivational model, a learner's independence is judged from the efforts he or she makes to solve the problems on his or her own without asking for help from others even if the student encounters some difficulty. The greater the numbers of sessions of work with the system and the greater the time spent on solving exercises gives an indication that learner was facing difficulty. Nonetheless, performing well on exercises without getting hints or help from the system at any stage offers an indication of the learner's independence.

Learning Styles and Affective States Tools Architecture

In this section we present a tool/framework for detecting learning styles and affective states, such as motivation and emotion based on a learner's behavior. The tools architecture is divided into two components as shown in Figure 4. The data in the database is stored in an event-based way, which simplifies the data extraction process from the database. The data extraction component is shown in figure 4.

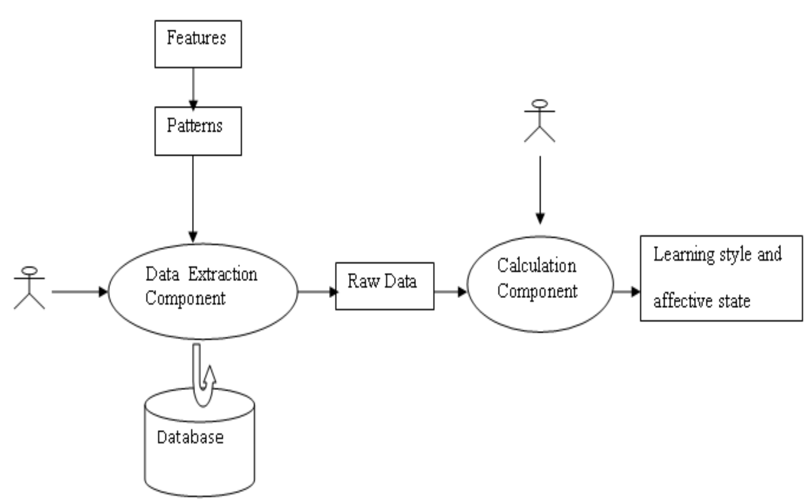

Figure 4. Detecting learning styles and affective states [Figure taken from Graf(2007)].

Calculation of Learning Styles and Affective States

Learning styles and affective states are calculated from the raw data extracted by the data extraction component. Learning styles are calculated in this way for each dimension based on the ordered data. Ordered data for each pattern can take the values +1, 0,-1, indicating, e.g. a balanced, moderate, or strong state. Affective states are also calculated for each aspect based on the ordered data. Ordered data for each pattern can also take the values +1, 0,-1 indicating a low, normal, or high state. The proposed tool recommends thresholds, which can be changed if necessary. These thresholds are based on (García et al. 2007) dealing with the usage of respective features.

Calculation of learning styles is based on the approach adopted in the ILS (Index of Learning Styles). According to this approach, the ordered data relevant to each dimension are summarized. Each dimension result is converted to a 3-item scale indicating, for example a balanced, moderate, or strong preference. Similarly, in the calculation of affective states, ordered data relevant to each aspect of the affective state are summarized. Each aspect of the affective state result is converted to a 3-item scale indicating low, normal, and high states.

Conclusion and Future Work

In this paper, we presented a student-driven learning and assessment tool along with learning styles and affective states detection/calculation tool. The learning and assessment tool enables both learning and assessment. The learning styles and affective states detection/calculation tool detects learning styles and affective states from the behavior of learners reflected in the database by the learning and assessment tool. Applying the proposed approach enables us to detect learning styles and affective states from the behavior of learners. Therefore, to obtain information about the learners' learning styles, learners' do not need to fill out a questionnaire. Also, it is not necessary to monitor observational cues, such as gesture, posture, conversation patterns, etc., of the learner to obtain information about a learner's affective states. The detection/calculation can be done automatically by the learning styles and affective states detection/calculation tool.

Future work deals with investigating the suitability of the selected patterns for the detection of learning styles and affective states, i.e., correlation between patterns of behavior and learning styles, affective states. Furthermore, we also plan to develop the proposed tool for the detection of learning styles and affective states.

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