

A New Approach to Discover Students Learning Styles in Adaptive Educational Systems

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Abstract. *Personalization according to specific requirements of an individual student is one of the most important features in adaptive educational systems. Considering learning and how to improve a student's performance, these systems must know the way in which an individual student learns best. In this context, the current work outlines a new approach to discover students learning styles, which is mainly based on the non-deterministic and non-stationary aspects of learning styles, taking into account that learning styles may change during the learning process in an unexpected and unpredictable way. Taking into consideration the stochastic and dynamic aspects enclosed on learning process, our approach gradually and constantly updates the student model using a set of rules that infer which learning styles should be adjusted at a specific moment. Therefore, the student model stochastically evolves towards the real student's learning style, considering its fine-tuned strengths. Our approach has been being tested through computer simulation of students and promising results have been obtained. Some of them are presented in this paper.*

1. Introduction

Learning Styles (LS) and their effects on learning processes are carefully exposed by Coffield [Coffield et al. 2009]. Their related instructional strategies have been being massively studied in the new learning space introduced by the Internet, where many researchers point out that linking LS to appropriate learning resources is an important stimulus for the learning process. Some researches reveal that a student's performance improves if the learning environment supports his/her specific LS. On the other hand, learners whose LS are not supported by the learning environment may have more difficulties during the learning process [Haider et al. 2010, Graf 2008, Kinshuk et al. 2009, Alfonseca et al. 2006, Graf et al. 2009, Felder and Silverman 1988].

In order to provide adaptivity, the student's characteristics have to be known first. However, the traditional approaches for detection of LS in Adaptive Educational Systems (AES) are inefficient. Price [Price 2004] analyzes the uncertainty aspect of Index of Learning Styles Questionnaire (ILS) by identifying inconsistencies between its results and the student's behavior. Besides Price, Roberts [Roberts and Erdos 1993] analyzes this kind of instrument and the problems related to it. Therefore, many approaches for automatic detection of LS have been being proposed. However, in general they present problems which make them either inefficient or difficult to implement, implant and use, as pointed out in section 2.

In this context, we propose a new approach to discover student's LS, which automatically detects and precisely adjusts students LS based on the non-deterministic and non-stationary aspects of LS, that may change during the learning process in an unexpected and unpredictable way [Graf and Kinshuk 2009]. Our approach is based on the Felder and Silverman Learning Styles Model (FSLSM) [Felder and Silverman 1988]. According to Graf and Kinshuk [Graf and Kinshuk 2009, Graf and Kinshuk 2010a], the FSLSM uses the concept of dimensions, and therefore describes LS in much detail. A very important characteristic of FSLSM to our work is that it uses scales to classify students instead of defined types. In this way, the strength of each LS is finely measured [Felder and Silverman 1988]. Therefore, our approach aims to gradually fine tune LS stored in student model (SM) along the learning process to efficiently optimize the SM. Another important aspect of FSLSM is that it considers preferences as tendencies and therefore, it takes into account that the student may act differently in specific situations, in a non-deterministic way, as pointed out by Kinshuk and Graf [Kinshuk et al. 2009] and by Graf and Kinshuk [Graf and Kinshuk 2009].

Therefore, we consider a student's preferences as probabilities in the four-dimensional FSLSM model, as depicted in section 3. As a result, our approach gradually, constantly and stochastically modifies the student's LS using a set of rules that detect which learning style should be adjusted at a specific moment. As a consequence, the SM effectively converges towards the real student's LS, as shown in section 4. Finally, section 5 presents conclusions and future work.

2. Related Works

A diversity of approaches for automatic detection of LS have been being proposed, such as [Graf and Liu 2008, Graf and Kinshuk 2010b, Castillo et al. 2005]. In general, these traditional approaches use deterministic inference systems for detecting student's learning styles through predefined patterns of behavior. These systems infer the LS based on the student's actions. A problem with these systems is the difficulty to develop rules that are able to infer LS effectively through student's actions and to treat the student's behavior as evidence and not as a possibility.

More complex approaches can be seen in [Kelly and Tangney 2005, García et al. 2007, Carmona et al. 2008, Cabada et al. 2009, Zatarain-Cabada et al. 2009, Zatarain et al. 2010, Carmona et al. 2007]. These approaches use learning machine techniques, such as Bayesian and neural networks. A problem with these approaches is their high complex implementations and high computation cost, which is a serious concern when there is a high number of simultaneous students using the system. Besides, in general, these approaches are highly coupled either to the system they were designed for or to the whole process aimed at selecting the suitable learning resources according to the student's specific characteristics, making them harder to re-use in other systems. In some of these approaches, once acquired, the student's LS remains the same throughout the entire learning process [Castillo et al. 2005].

Another well-known problem with learning machine approaches is the complication generated by concept drift and concept shift [Castillo et al. 2005]. They occur either because the acquired LS information needs to be adjusted or because the student simply changes his/her preferences. In this scenario, adaptive decision models that are able to

better fit student's preferences are desirable.

In this context, we believe that our approach brings advantages due to some specific characteristics:

- the consideration that not only LS but many factors have an influence on student's performance (knowledge and behavior), making it harder to infer the student's LS based only on fixed behavioral pattern rules. Some of these factors are pointed out in [Haider et al. 2010, Graf 2008, Kinshuk et al. 2009, Alfonseca et al. 2006, Graf et al. 2009];
- the consideration that student's LS can change over time in an unpredictable way [Graf and Kinshuk 2009] and that these changes may be associated with other factors, such as knowledge domain, as analyzed by Jones [Jones et al. 2003];
- the consideration that as pointed out in [Price 2004], it's impossible to know about the correctness of results obtained from self-assessment questionnaires, where a deterministic process should take a very long time to detect inconsistencies or never detect it;
- eliminating the necessity of discovering a student's behavioral patterns, considering that it's hard to obtain such patterns. They may have inconsistencies and they make the student modeling process deterministic;
- being uncoupled from any Learning Management System (LMS), being independent of students actions in a specific system, as it occurs in traditional approaches, as [García et al. 2007, Graf and Liu 2008];
- the consideration that LS have a dynamic nature, and they may change when the knowledge domain changes [Kelly and Tangney 2005] or naturally evolve with time [Messick 1976];

The next section presents important aspects of our approach.

3. Proposed Approach

This approach is based on probabilistic learning styles combinations [Franzoni and Assar 2009] and on the approach depicted in [Dorça et al. 2011]. A learning style combination (LSC) is a 4-tuple composed by one LS from each FLSM dimension, as stated by Definition 3.1.

Definition 3.1 *Learning Styles Combination (LSC)*

$$LSC = \{(a, b, c, d) / a \in D1, b \in D2, c \in D3, d \in D4\}$$

where:

$$D1 = \{Active(A), Reflective(R)\}$$

$$D2 = \{Sensitive(S), Intuitive(I)\}$$

$$D3 = \{Visual(Vi), Verbal(Ve)\}$$

$$D4 = \{Sequential(Seq), Global(G)\}$$

Therefore, there are 16 possible learning styles combinations, as stated by Definition 3.2.

Definition 3.2 *Learning Styles Combinations (LSCs)*

$$LSCs = \{(A, Vi, S, Seq), (A, Vi, S, G), (R, Vi, S, Seq), (R, Vi, S, G), (A, Ve, S, Seq), (A, Ve, S, G), (R, Ve, S, Seq), (R, Ve, S, G), (A, Vi, I, Seq), (A, Vi, I, G), (R, Vi, I, Seq), (R, Vi, I, G), (A, Ve, I, Seq), (A, Ve, I, G), (R, Ve, I, Seq), (R, Ve, I, G)\}.$$

We propose that during a learning section the student should interact with a set of learning objects (LO) [IEEE 2010] that satisfies a specific LSC, stochastically selected according to the student's LS preferences stored in the SM. Which means that, in our approach, a LSC is a specific combination of four random variables [Papoulis et al. 2002]. Therefore, in our approach, the student's LS describes the probability of random variables a, b, c and d, considering Definition 3.1.

In this context, student's LS are stored as values in the interval [0..100] instead of [-11..+11] representing a student's probability of preference for a specific LS in a FSLSM dimension. Therefore, the student's preferences are stored as probabilities. Using this approach, a student's LS are represented according to Definition 3.3.

Definition 3.3 *Learning Styles (LS)*

$$LS = \{(Pr_A, Pr_R), (Pr_S, Pr_I), (Pr_{Vi}, Pr_{Ve}), (Pr_{Seq}, Pr_G) / Pr_A + Pr_R = 100, Pr_S + Pr_I = 100, Pr_{Vi} + Pr_{Ve} = 100, Pr_{Seq} + Pr_G = 100\}$$

For example, considering a student's $LS = \{(35.0, 65.0), (17.0, 83.0), (89.0, 11.0), (84.0, 16.0)\}$ we can consider that this student **probably** is (R)effective, (I)ntuitive, (Vi)sual and (Seq)quential. Taking into consideration that LS are probabilities, a LSC has a probability to be selected during a learning section which is equal to the student's probabilistic preference (P) for the LSC. For example, considering the student's LS above, we have $P(R, I, Vi, Seq) = 0.83 \times 0.89 \times 0.65 \times 0.84 = 0.403(40.3\%)$. In this context, the most advantage of our approach is to stochastically consider all LSC's according to the student's **supposed** LS, that **may** be wrong or **may** change over time, as pointed out in 2. As shown in section 4, this characteristic allows to effectively discover and fine-tune the real student's LS.

The selection of a LSC is done through the Roulette Wheel Selection method [Goldberg 1989], due to its adequacy to our approach. A binary representation of LSCs is used, where preferences A, S, Vi, Seq are represented by 0 and preferences R, I, Ve, G are represented by 1. Therefore, we have the following LSCs = $\{(0,0,0,0), (0,0,0,1), (1,0,0,0), (1,0,0,1), (0,1,0,0), (0,1,0,1), (1,1,0,0), (1,1,0,1), (0,0,1,0), (0,0,1,1), (1,0,1,0), (1,0,1,1), (0,1,1,0), (0,1,1,1), (1,1,1,0), (1,1,1,1)\}$. After each learning section, we apply recombination and mutation operators, based on genetic algorithms [Chipperfield et al. 1994]. The recombination operator recombines LSC's in order to (probably) produce more fitted LSC.

We are using here the single-point crossover [Chipperfield et al. 1994]. This crossover operation is not necessarily performed on all strings in population. Instead, it is applied with a probability P_x when the pairs are chosen for breeding. The mutation operator is then applied to the new LSC with a probability P_m (mutation rate).

It's important to consider that LS stored in SM are constantly updated as follows. When the student shows a learning problem during a learning section, the student's preferences in SM that accords to the selected LSC are decremented, considering a probable inconsistency in these preferences. The student's preferences in SM that discords to the selected LSC are incremented, making them stronger, considering that the learning difficulties appeared because they were not present in the selected LSC.

While these updates are executed, LS in SM becomes more consistent and, consequently, the student's most appropriate LSC becomes more and more fitted. Therefore,

adaptivity becomes more accurate and the student's performance is improved, as it is shown in next section. A coefficient K_c , that takes into account the distance between student's LS (DLS) in a specific dimension and the student's performance (PFM) on the current learning section, is used in order to calculate the updated LS to be stored in SM after a learning section. K_c is calculated as shown in (1), where K is a constant ($K = 10$). DLS is calculated as shown in (2).

$$K_c = \frac{K}{PFM \times DLS} \quad (1)$$

$$DLS = |SM[d_i]_A - SM[d_i]_B| \quad (2)$$

Therefore, as we can see, while the PFM value is less, the K_c value is greater. And while the DSL value is greater, the K_c value is less. These rules for gradually fine tune the LS are based on Reinforcement Learning [Kaelbling et al. 1996] and Simulated Annealing [Kirkpatrick et al. 1983] techniques and they are a critical part of our work, which is still being adjusted.

It's well-known that a variety of factors should be taken into account for calculating student's performance, as pointed out in [Dorça et al. 2009, Lopes et al. 2008]. It's a complex problem and a lot of approaches have been being proposed to solve it. For testing our approach without this complexity, we developed a student simulator that calculates student's performance taking into account some aspects related to the impact of LS on student's performance, as depicted in [Haider et al. 2010, Graf 2008, Kinshuk et al. 2009, Alfonseca et al. 2006, Graf et al. 2009]. Simulating students is a widespread and widely used technique for testing educational systems [Abdullah and Cooley 2002, Vanlehn et al. 1994, Vizcaino and du Boulay 2002, Virvou et al. 2003, Bravo and Ortigosa, Mertz 1997, Meyn et al. 1996]. The student simulator is not focused on this paper and it will be depicted at another opportunity. The next section presents some experiments and discusses the results.

4. Testing the proposed approach

The proposed approach has been being tested through a set of experiments. Some of them are expounded in this section and their results are discussed. The experiments expounded in this section were executed considering population size equal to 100 (where the first 16 individuals are copied from LSCs - see Definition 3.2 - and the rest of the individuals are randomly generated; $P_x = 0.2$; $P_m = 0.1$).

This configuration has shown good results. Other configurations have been being tested. Each experiment was repeated 20 times so that we could observe our approach working under different circumstances but under identical conditions. It was possible to notice that the resulting sequences during an experiment were different, but the final results were very, very similar. So, the non-determinism and convergence aspects intrinsic to the learning and student modeling processes were very clear.

In each experiment we considered different initial assumptions about the student's LS. In addition, we set the real student's LS, used by the student simulator. The simulator needs to know the real student's LS (R_{LS}) and the strength of each one (strong, moderate or weak). Four experiments and their results are shown in this section. The execution of an experiment finishes when the student achieves all learning goals, as explained in section 3.

We considered 30 concepts to be learned by students with 6 cumulative cognitive levels to be achieved in each concept based on the Bloom's Taxonomy [Chang and Chung 2010]. As the learning process becomes harder, more iterations are necessary to achieve the learning goals.

First, we considered a student with the following R_{LS} : $R_{LS} = \{ \text{reflective (strong), sensitive (strong), visual (moderate), global (weak)} \}$. The student's LS in SM are initially defined as: $LS = \{(70.0, 30.0), (35.0, 65.0), (60.0, 40.0), (45.0, 55.0)\}$. As can be seen, LS are initially inconsistent and doesn't express all the student's preferences correctly, specifically in dimensions active/reflective and sensitive/intuitive. Figure 1 presents one execution of this experiment and shows how the student's LS changes along the learning process's iterations. All repetitions in this experiment produced a consistent SM through a different path, due to the non-deterministic aspect of the student modeling process. As

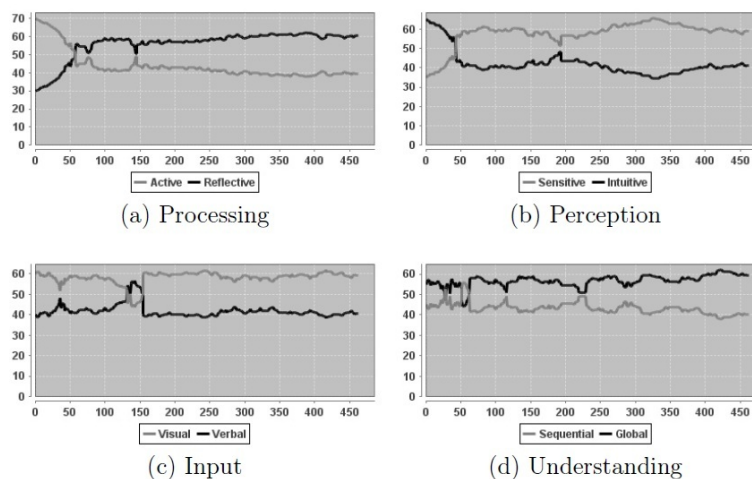


Figure 1. Results from experiment 1.

can be seen in Figure 1 approximately 460 iterations were necessary to finish the learning process, which is a high number when compared to the next experiment. It shows considerable learning difficulties by the student, considering that two strong preferences were initially inconsistent in SM.

In the following experiment, we consider the case in which there are no initial information available about the student's LS: $LS = \{(50.0, 50.0), (50.0, 50.0), (50.0, 50.0), (50.0, 50.0)\}$. The student's real LS are: $R_{LS} = \{ \text{reflective (weak), intuitive (strong), visual (moderate), sequential (weak)} \}$. Figure 2 presents the results obtained from an execution of this experiment. Figure 2 shows that less iterations were necessary to complete the simulated learning process. This occurred because inconsistencies in SM seemed to be worse than the lack of information. When the system doesn't have any initial information available about student's LS it can discover preferences faster and provide accurate adaptivity earlier. All repetitions of this experiment produced consistent LS.

Finally, we believe that the results obtained from these experiments validate the proposed approach, which can be easily implemented in an existing LMS, like Moodle [Moodle 2010] and SIMEduc [Dorça et al. 2002, Dorça et al. 2003, Dorça et al. 2004], and tested with real students. Simulating students was a very important part of our work

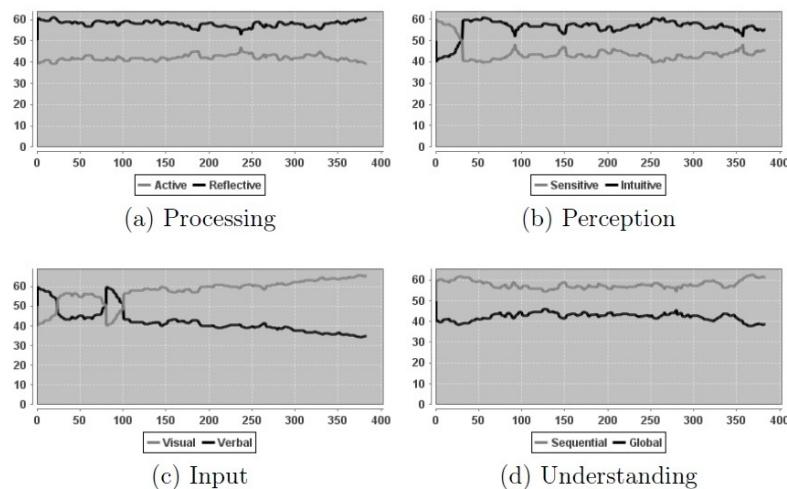


Figure 2. Results from experiment 2.

because it allowed us to test, adjust and correct our design since the very beginning, optimizing the development process.

5. Conclusion and Future Works

AES has been being considered as a promising approach to increase the efficiency in computer-aided learning. A necessary characteristic in this approach is the precise, dynamic and continuous identification of a student's LS in order to provide well-adapted learning experiences. In this context, one challenge is the development of systems able to efficiently acquire a student's LS. The information about a student's LS acquired by psychometric instruments encloses some degree of uncertainty [Price 2004, Roberts and Erdos 1993]. Furthermore, in most of the existing approaches, the assumptions about the student's LS, once acquired, are no longer updated.

In this context, this work presents a new approach to automatically detect and precisely adjust a student's LS based on the non-deterministic and non-stationary aspects of LS, that may change during the learning process in an unexpected and unpredictable way [Graf and Kinshuk 2009]. Because of the probabilistic and dynamic factors enclosed on automatic detection of LS, our approach gradually and constantly modifies the SM using a set of rules that detect which LS should be adjusted at that moment, considering the student's performance. In this manner, the SM converges towards the real student's LS, considering fine-tuned strengths, as shown in section 4.

Finally, the proposed approach solves some important problems ignored in most of the analyzed approaches and brings advantages, due to specific points, as shown in section 2. The validation was done through the computer simulation of students, which took into account some important aspects on how LS influences a student's performance as described by some researchers, e.g., [Haider et al. 2010, Graf 2008, Kinshuk et al. 2009, Alfonseca et al. 2006, Graf et al. 2009]. Evaluation of AES is a difficult task, as pointed out in [Bravo and Ortigosa]. Therefore, the validation of our model through simulation was vital, due to the time and human resources needed to test real students. Now that we have achieved good results through simulation, we feel safe to use our approach in an existing LMS, like Moodle [Moodle 2010], and test it with real courses and students.

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