Chapter 15
Evolutionary Approach for Automatic and Dynamic Modeling of Students' Learning Styles

Fabiano Azevedo Dorça
Federal University of Uberlandia, Brazil

ABSTRACT

Most of the distance educational systems consider only little, or no, adaptivity. 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, this chapter depicts an application of evolutionary algorithms to discover students' learning styles. The approach is mainly based on the non-deterministic and non-stationary aspects of learning styles, which may change during the learning process in an unexpected and unpredictable way. Because of the stochastic and dynamic aspects enclosed in learning process, it is important to gradually and constantly update the student model. In this way, the student model stochastically evolves towards the real student's learning style, considering its fine-tuned strengths. This approach has been tested through computer simulation of students, and promising results have been obtained. Some of them are presented in this chapter.

INTRODUCTION

Most of the distance education systems don't take into account the individual student's characteristics. As a consequence, the same learning objects, pedagogical strategies and learning resources are commonly used for everybody. However, adaptivity (Brusilovsky, 2001) has been introduced in these systems during the last years in order to provide individual learning experience (Graf and Kinshuk, 2009). In this way, the main student's characteristics considered in the personalization of a course are: learning goals (Chang and Chung, 2010), cognitive level (Chang and Chung, 2010), interests (Brusilovsky, 2001), stereotypes (Zakaria and Brailsford, 2002) and learning styles (LS)

DOI: 10.4018/978-1-4666-6276-6.ch015

(Felder and Silverman, 1988). The use of LS in adaptive educational systems (AES) is motivated by educational and psychological theories, which argue that learners have different ways in which they prefer to learn (Graf and Kinshuk, 2009).

Learning Styles and their effects on learning processes are carefully exposed by Coffield et al. (2009). Instructional strategies have been 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 et al., 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 AES are inefficient. Price (2004) analyzes the uncertainty aspect of ILSQ (Index of Learning Styles Questionnaire) by identifying inconsistencies between its results and students behaviors. Besides Price, 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 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 present in this chapter an evolutionary approach to discover students LS which uses a probabilistic student model and a genetic algorithm. This approach is based on the non-deterministic and non-stationary aspects of LS, which 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's Learning Styles Model (FSLSM) (Felder and Silverman, 1988). According to Graf and Kinshuk (2009, 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 the student model along the learning process, using a genetic algorithm (Chipperfield et al., 1994) to efficiently optimize students LS. 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 et al. (2009); Graf and Kinshuk (2009).

Therefore, we consider a student's preferences as probabilities in the four-dimensional FSLSM model, as depicted in section 4. As a result, our approach gradually, constantly and stochastically modifies students LS using a set of rules in order to detect which LS should be adjusted at a specific moment. As a consequence, student model effectively converges towards real student's LS, as shown in section 5. Finally, section 6 presents conclusions and future work.

RELATED WORKS

A diversity of approaches for automatic detection of LS have been 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 students LS through predefined behavioral patterns. These systems infer LS based on students actions. A problem with these systems is the difficulty in the development of rules able to