Adaptivity and Personalization in Learning Systems based on Learning Styles*

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Abstract. Providing learners with personalized recommendations and/or adaptive courses that fit their characteristics has high potential to make online learning easier and more effective for learners. However, most of the learning systems that are currently used by educational institutions do not provide adaptivity based on learners' characteristics or needs. This paper focuses on the consideration of learning styles in learning systems and introduces approaches and mechanisms that enable existing learning systems to identify learners' learning styles, using automatic and dynamic learner modelling for building and frequently updating learners' learning styles based on data about learners' behaviour in a course. Furthermore, the paper discusses how the information about learners' learning styles can be used and introduces adaptive mechanisms that enable learning systems to automatically generate courses that fit learners' learning styles. The introduced approaches and mechanisms aim at extending existing systems with adaptivity and personalization, and therefore, allowing teachers to continue teaching their courses in the respective learning systems and additionally providing support for learners through provision of adaptivity and personalization based on learning styles.

1 Introduction

Nowadays, more and more educational institutions, such as universities, offer e-learning courses. However, when looking at the learning systems that are used for providing such e-learning courses, mostly so-called learning management systems, it can be seen that these systems typically use a one-size-fits-all approach, treating all learners in the same way without providing adaptive or personalized support.

This paper focuses on the consideration of learning styles in learning systems. Research about considering learning styles in technology enhanced learning is motivated by educational and psychological theories, which argue that learners have

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different ways in which they prefer to learn. Furthermore, Felder, for example, pointed out that learners with a strong preference for a specific learning style may have difficulties in learning if the teaching style does not match with their learning style [1, 2]. From theoretical point of view, conclusion can be drawn that incorporating learners' learning styles in a learning environment makes learning easier for learners and increases their learning efficiency. On the other hand, learners whose learning styles are not supported by the learning environment may experience problems in the learning process.

Based on these theoretical arguments, several adaptive learning systems have been developed over the last years. Examples of such systems include CS383 [3], WELSA [4], and TSAL [5]. Evaluations of these systems demonstrated the possible benefits of considering learning styles in learning systems, showing that the required time for learning can be decreased and the overall learner satisfaction can be increased. Although these adaptive systems seem to support learners very well, and therefore demonstrate that considering learning styles can help learners in learning, the systems which are currently used by most educational institutions typically do not consider individual differences and in particular do not consider learning styles.

In this paper, we demonstrate approaches and mechanisms for enhancing existing (and commonly used) learning systems by enabling them, on one hand, to identify learning styles and, on the other hand, to provide adaptive and personalized courses and/or recommendations to learners once their learning styles have been identified. These approaches and mechanisms are based on the Felder-Silverman learning style model (FSLSM) [1], which proposes that each learner has a preference for each of its four dimensions: the active/reflective, sensing/intuitive, visual/verbal, and sequential/global dimension.

In the next section, this paper focuses on automatic student modelling and how to identify learners' learning styles based on learners' behaviour in an online course. Subsequently, dynamic aspects of identifying learning styles are discussed, showing how learning styles can be frequently updated while learners are learning. In the next section, we introduce mechanisms for extending learning systems and enabling them to providing adaptive and personalized courses based on learners' learning styles.

2 Automatic Student Modelling of Learning Styles

The first step towards incorporating learning styles in technology enhanced learning is to identify learners' learning styles. Brusilovsky [6] distinguished between two different ways of student modelling: *collaborative* and *automatic*. In the collaborative approach, the learners provide explicit feedback which can be used to build and update a student model, such as filling out a learning style questionnaire. In the automatic approach, the process of building and updating the student model is done automatically based on the behaviour and actions of learners while they are using the system for learning. The automatic approach is direct and free from the problem of inaccurate self-conceptions of learners. Moreover, it allows learners to focus only on learning rather than additionally providing explicit feedback about their preferences. In contrast to learning style questionnaires, an automatic approach can also be more accurate and less error-prone since it analyses data from a time span rather than data which are gathered at one specific point of time.

Due to the advantages of identifying learning styles through automatic student modelling, an automatic approach has been designed, implemented and evaluated [7], which uses the behaviour and actions of learners, gathered while they are learning, for inferring their learning styles with respect to the FSLSM. An important aim of this approach was that it should be applicable for different learning systems.

Only few research works exist about automatic identification of learning styles in learning systems (e.g., [8, 9]). These works aim at identifying learning styles in particular learning systems and therefore are tailored exactly to these systems by using only those behaviour patterns which are incorporated in the respective systems. Moreover, the investigated courses are created in consideration of learning styles by using particular types of learning objects for detecting learning styles.

When aiming at developing a generic approach for automatic student modelling which can be used for different learning systems, several additional issues have to be considered. First, behaviour patterns have to be selected in a way that most learning systems are able to gather data with respect to these patterns. Furthermore, it needs to be noted that most courses in existing learning systems are not created in consideration of learning styles. Therefore, it is not sufficient that the system can technically track the required information about patterns but teachers also have to use the respective types of learning objects in their courses. Hence, only commonly used types of learning objects were selected as basis for patterns in the automatic student modelling approach. Moreover, the approach has to consider that nevertheless some data might not be available and therefore has to be able to deal with missing data. Thus, the proposed approach considers a high number of patterns, which is beneficial for identifying learning style accurately.

For each of the four learning style dimensions of FSLSM, relevant behaviour patterns were selected, which were based on commonly used types of learning objects in learning systems. For inferring learning styles from the behaviour and actions of learners, a data-driven approach using Bayesian networks and a literature-based approach using a simple rule-based method were implemented. In a study with 127 students, who participated in a university course about object oriented modelling within the learning management system Moodle, both approaches were evaluated. The learning styles calculated from both approaches were compared with the results of the ILS questionnaire [2], a 44-item instrument developed by Felder and Soloman for identifying learning styles based on the FSLSM. The evaluation showed that the literature-based approach achieved better results (precision values of the four dimensions ranged from 73.33% to 79.33%) than the data-driven approach (precision values ranged from 62.5% to 68.75%) and identified learning styles with high precision. Hence, the proposed concept including the literature-based approach can be seen as a suitable instrument for automatic detection of learning styles.

The concept for identifying learning styles through the literature-based approach was implemented in a standalone tool called DeLeS [7]. DeLeS automatically extracts relevant data from a learning system’s database and calculates learning styles by using the literature-based approach.

3 Dynamic Student Modelling of Learning Styles

Besides distinguishing between collaborative and automatic student modelling, student modelling can be classified as *static* or *dynamic*. Static student modelling refers to an approach where the student model is initialised only once (mostly when learners register in the system). In contrast, a dynamic student modelling approach frequently updates the information in the student model and therefore allows responding to changes of the investigated learner characteristic such as learning styles. A dynamic approach has two advantages over a static one in the context of identifying learning styles. First, dynamic student modelling can consider exceptional behaviour of learners and therefore can extend static student modelling by incrementally improving and fine-tuning the information in the student model, learning the learning styles of learners until they have been identified reliably. Second, since many of the major learning style models such as FSLSM argue that learning styles can change over time, dynamic student modelling allows monitoring learners' behaviour, identifying changes in their learning styles, and updating the learning styles in the student model respectively.

In order to consider dynamic student modelling in learning systems, an architecture has been designed that aims at enabling existing learning systems to build and frequently update learners' learning styles based on FSLSM. Therefore, learners' actions in the learning system are monitored and once a learner performed a pre-defined amount of actions, his/her learning styles are re-calculated through automatic student modelling based on his/her recent behaviour. After this recalculation of learning styles, the result is analysed in the context of the currently stored learning styles of a learner as well as the results of previous re-calculations. For deciding whether an update of learners' learning styles is required, a mathematical model has been designed and verified [10] that aims at reaching two partially conflicting objectives. On one hand, the currently stored information in the student model should reflect the current learning styles of learners as good as possible and therefore should be updated as soon as a revision can be done. On the other hand, deviations of learners' behaviour have to be considered and the student modelling approach should avoid situations where the learning styles of learners are revised and then briefly afterwards this revision has to be taken back.

Additionally, static student modelling is integrated in the architecture, providing learners the option to fill out the ILS learning style questionnaire. Such static data can be used for initializing the student model, while dynamic student modelling is then used for fine-tuning and updating the learners' learning styles from their behaviour.

The modules of the architecture are designed to be as independent as possible with respect to the learning system, so that they can be integrated in different systems. In order to use the information about learners' learning styles, adaptivity modules can be added to the learning system. These modules can access the learners' learning styles and use this information, for example, for providing learners with adaptive recommendations and/or adapting courses to learners' learning styles.

The proposed architecture has been implemented in a learning system and tested with an adaptivity module that provides learners with adaptive feedback about their learning styles and how to improve their learning processes considering their learning styles and their enrolled courses.

4 Adaptive Course Provision based on Learning Styles

Once learners' learning styles are identified, this information can be used for providing adaptive support such as adaptive courses that match learners' learning styles. In order to provide learners with such adaptive courses, an adaptive mechanism has been designed, implemented and evaluated [11]. This mechanism aims at enabling learning systems to automatically generate adaptive courses and, at the same time, asking teachers for as little as possible additional work. The adaptive mechanism is based on a concept that assumes the existence of certain, commonly used types of learning objects, including content, outlines, conclusions, examples, exercises and self-assessment tests, and then composes courses for each learner automatically using adaptive sequencing and adaptive hiding techniques. This concept is developed in a way that it can be used for different learning systems but was implemented for Moodle and evaluated by a university course about object oriented modelling with 437 students. From the analysis of the learners' performance and behaviour in the course, we found that learners who learned from a course that matches their learning styles spent significantly less time in the course and achieved in average the same grades than learners who got a course that either mismatched their learning styles or included all available learning objects [11]. Therefore, providing adaptive courses according to the proposed concept can be seen as effective in supporting learners in learning.

Furthermore, more detailed analysis was performed with respect to the effects and effectiveness of adaptivity for learners with different learning styles [12]. The results showed that learners with different learning styles benefit from adaptivity in different ways and extents. The findings provide deeper insights and help in understanding the effects and effectiveness of adaptive courses, considering different learning styles.

In addition, the adaptive mechanism has been extended to be more flexible for teachers, making it easier for teachers to use the mechanism for their existing courses. Therefore, the concept of providing adaptivity has been extended with respect to adding more types of learning objects in order to support a variety of learning resources and activities. While teachers can use all of these types of learning objects, they are not required to use all of them nor are they required to use them in every section. Furthermore, the techniques for providing adaptivity were modified, using adaptive sequencing and adaptive annotating. The extended adaptive mechanism [13] has been implemented in Moodle for an introductory course on Computing and Information Systems, demonstrating that the adaptive mechanism can be easily used for different types of courses, such as practical courses (as the course on object-oriented modelling) and theoretical courses (such as the introductory course).

5 Conclusions

This paper discusses approaches and mechanisms for considering learning styles in learning systems. The aim of these approaches and mechanisms is to enable existing learning systems to automatically identify learning styles as well as to provide learners with adaptive courses. As a result, the concept of adaptivity and personalization should be brought closer to today's online learning, enabling teachers to continue using their courses in existing learning systems and additionally providing learners with personalized and adaptive learning experiences.

Future work will deal with extending our research to different settings such as mobile and ubiquitous learning environments as well as considering not only learning styles but also other learners' characteristics such as cognitive abilities, motivational aspects, affective states, the context in which a learner is learning and others, in order to provide learners with rich adaptivity and personalization.

References

1. Felder, R.M., Silverman, L.K.: Learning and teaching styles in engineering education. Engineering Education 78(7), 674–681 (1988)
2. Felder, R.M., Soloman, B.A. (1997). *Index of Learning Styles questionnaire*. Retrieved 4 August, 2010, from http://www.engr.ncsu.edu/learningstyles/ilsweb.html
3. Carver, C.A., Howard, R.A., Lane, W.D.: Addressing different learning styles through course hypermedia. IEEE Transactions on Education 42(1), 33-38 (1999)
4. Popescu, E.: Dynamic adaptive hypermedia systems for e-learning. Ph.D. thesis, Université de Craiova, Romania (2008)
5. Tseng, J.C.R., Chu, H.-C., Hwang, G.-J., Tsai, C.-C.: Development of an adaptive learning system with two sources of personalization information. Computers & Education 51(2), 776–786 (2008)
6. Brusilovsky, P.: Methods and techniques of adaptive hypermedia. User Modeling and User-Adapted Interaction 6(2-3), 87-129 (1996)
7. Graf, S., Kinshuk, Liu, T.-C.: Supporting teachers in identifying students' learning styles in learning management Ssystems: An automatic student modelling approach. Educational Technology & Society 12(4), 3-14 (2009)
8. García, P., Amandi, A., Schiaffino, S., Campo, M.: Evaluating Bayesian networks' precision for detecting students' learning styles. Computers & Education 49(3), 794-808 (2007)
9. Cha, H.J., Kim, Y.S., Park, S.H., Yoon, T.B., Jung, Y.M., Lee, J.-H.: Learning style diagnosis based on user interface behavior for the customization of learning interfaces in an intelligent tutoring system. In: Proceedings of the International Conference on Intelligent Tutoring Systems, LNCS vol. 4053, pp. 513-524. Springer, Heidelberg (2006)
10. Graf, S., Kinshuk: An approach for dynamic student modelling of learning styles. In: Proceedings of the International Conference on Exploratory Learning in Digital Age, pp. 462-465. IADIS Press, Rome, Italy (2009)
11. Graf, S., Kinshuk: Providing adaptive courses in learning management systems with respect to learning styles. In: Proceedings of the World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education, pp. 2576-2583. AACE Press, Chesapeake, VA (2007)
12. Graf, S., Lan, C.H., Liu, T.-C., Kinshuk: Investigations about the effects and effectiveness of adaptivity for students with different learning styles. In: Proceedings of the IEEE International Conference on Advanced Learning Technologies, pp. 415-419. IEEE Computer Society, Riga, Latvia (2009)
13. Graf, S., Kinshuk, Ives, C.: A Flexible Mechanism for Providing Adaptivity Based on Learning Styles in Learning Management Systems. In: Proceedings of the IEEE International Conference on Advanced Learning Technologies, pp. 30-34. IEEE Computer Society, Sousse, Tunisia (2010)