Providing Adaptive Courses in Learning Management Systems with Respect to Learning Styles*

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Abstract: Learning management systems (LMS) are commonly used in e-learning but provide little, or in most cases, no adaptivity. However, courses which adapt to the individual needs of students make learning easier for them and lead to a positive effect in learning. In this paper, we introduce a concept for providing adaptivity based on learning styles in LMS. In order to show the effectiveness of our approach, Moodle was extended by an add-on and an experiment with 437 students was performed. From the analysis of the students' performance and behaviour in the course, we found out that students who learned from a course that matches their learning styles spent significantly less time in the course and achieved in average the same marks than students who got a course that either mismatched with their learning styles or included all available learning objects. Therefore, providing adaptive courses in LMS according to the proposed concept can be seen as effective in supporting students in learning.

Introduction

A lot of research has been done dealing with investigating and developing adaptive systems which aim at providing courses that fit to the individual needs of learners (Brusilovsky 1996; Sadat & Ghorbani 2004). Adaptation techniques can be distinguished between adaptive presentation support and adaptive navigation support. Adaptive presentation includes adaptation features based on content such as adaptive multimedia presentation and adaptive text presentation, whereas adaptive navigation is based on links and includes features such as direct guidance as well as adaptive sorting, hiding and annotating of links. Furthermore, adaptivity can be provided based on different characteristics of learners. For instance, a system can incorporate the prior knowledge, the learning goals, the cognitive abilities, and the learning styles of students.

In this paper, we focus on adaptivity based on learning styles. Learning style can be defined as characteristic strengths and preferences in the ways learners take in and process information (Felder 1996). Different possibilities exist for adapting a course based on the learning styles of students. The most often used approach is to match the instructions to the preferences or abilities of the learners and teach according to the learners' strengths. This approach aims at a short-term goal namely to make learning as easy as possible at the time learners are using the system. Looking at long-term goals, Messick (1976) suggested that learners should also train their not-preferred skills and preferences. He argued that when learners acquire more educational experience, they are required to adapt to a variety of instructional methods and styles. The ability to adapt to different instructional styles will prepare them with important life skills. For example, providing verbal learners with only visual forms of instruction forces them to develop and use visual skills.

A number of adaptive systems exist, which focus on providing courses that fit to the learning styles of the students. Examples of such systems include CS383 (Carver, Howard, & Lane 1999), IDEAL (Shang, Shi, & Chen 2001), MAS-PLANG (Peña, Marzo, & de la Rosa 2002), TANGOW (Paredes & Rodríguez 2004), and AHA! (Stash, Cristea, & de Bra 2006). However, adaptive systems have some limitations, for example, they lack integration, supporting only few functions of web-enhanced education, and the content of courses is not available for

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reuse (Brusilovsky 2004). On the other hand, learning management systems (LMS) such as WebCT (2006), Blackboard (2007), and Moodle (2007) are commonly and successfully used in e-learning. They provide a variety of features to support teachers and course developers to create and manage their online courses. However, at current stage, typical LMS provide only little, or in most cases, no adaptivity.

In this paper, we combine the advantages of LMS and adaptive systems by introducing a concept for enhancing LMS with adaptivity based on learning styles (described in Section 2). We used the open source LMS Moodle as a prototype and developed an add-on that enables Moodle to automatically provide adaptive courses that fit to the learning styles of the students. This add-on is described in Section 3. In order to prove the effectiveness of our extensions, we performed an experiment with 437 students who used the adaptive version of Moodle. Section 4 presents the experiment and discusses its results. Section 5 concludes the paper.

A Concept for Providing Adaptivity based on Learning Styles

In this section, we introduce a concept for providing adaptivity in LMS with respect to learning styles according to Felder-Silverman learning style model (FSLSM) (Felder & Silverman 1988). While several different learning style models exist in literature, for example the model by Kolb (1984) and Honey and Mumford (1982), FSLSM is one of the most often used model in adaptive educational systems in recent times and some researchers even argue that FSLSM is the most appropriate model for use in adaptive systems (Carver et al. 1999; Kuljis & Liu 2005). Most other learning style models classify learners in few groups, whereas FSLSM describe the learning style of a learner in more detail, distinguishing between preferences on four dimensions: active/reflective, sensing/intuitive, visual/verbal, and sequential/global. For each dimension, a value from +11 to -11 indicates the preference on the respective dimension. These values represent tendencies, saying that even a learner with, for example, a strong active learning style can act sometimes in a reflective way.

For the proposed concept, we included only three of the four dimensions of FSLSM, namely the active/reflective, sensing/intuitive, and sequential/global dimension. We excluded the visual/verbal dimension since we aim at minimizing the additional effort of course developers and this dimension would ask for different presentation modes, for example, including text, audio-files, video-files and so on. Moreover, in order to keep the concept system-independent and to avoid asking too much from the course developers, only commonly used course elements of LMS are incorporated.

In the following subsection, we describe the required course elements for providing adaptive courses. These elements are based on a meta-model for adaptive courses in LMS (Graf 2005). Subsequently, we show how adaptivity regarding learning styles can be provided based on the introduced course elements.

Course Elements

The concept for providing adaptivity is based on specific course elements. In general, we assume a course structure consisting of several chapters, where for each chapter, adaptivity can be provided. Each chapter includes an *outline* of the presented topics in the chapter as well as a *conclusion* that summarizes the most important aspects of the chapter. For presenting the content of the course, *content objects* are considered which are pages that include the relevant learning materials. Furthermore, we incorporate *examples* as course elements. Examples are used for better illustration and provide students with more concrete material. Moreover, students can check their acquired knowledge by the use of *self-assessment tests*. Another element includes *exercises* which serve as practice area where students can try things out or answer questions about interpreting predefined solutions or developing new solutions.

Adaptation Features

Adaptation features indicate how a course can change for students with different learning styles. These features are based on the above described course elements and refer to the sequence and the number of presented elements. The general structure of the course can be seen in Figure 1. The adaptation features include the sequence of examples, exercises, and self-assessment tests and determine whether they are presented before the content objects, after the content objects or at both positions. Another adaptation feature is the number of presented examples and exercises. Moreover, we adapted the use of outlines by either presenting them only once before the content objects or additionally between topics in order to provide students with a better overview. Furthermore, the conclusion can be presented either after the content objects in order to summarize the learned material before applying the knowledge for other tasks (e.g. exercises) or they are presented at the end of the chapter in order to give students a final summary of the chapter. In the following paragraphs, we describe the incorporated learning style dimensions in more detail and show how the introduced adaptation features can be used to suit the learning style preferences of each dimension.

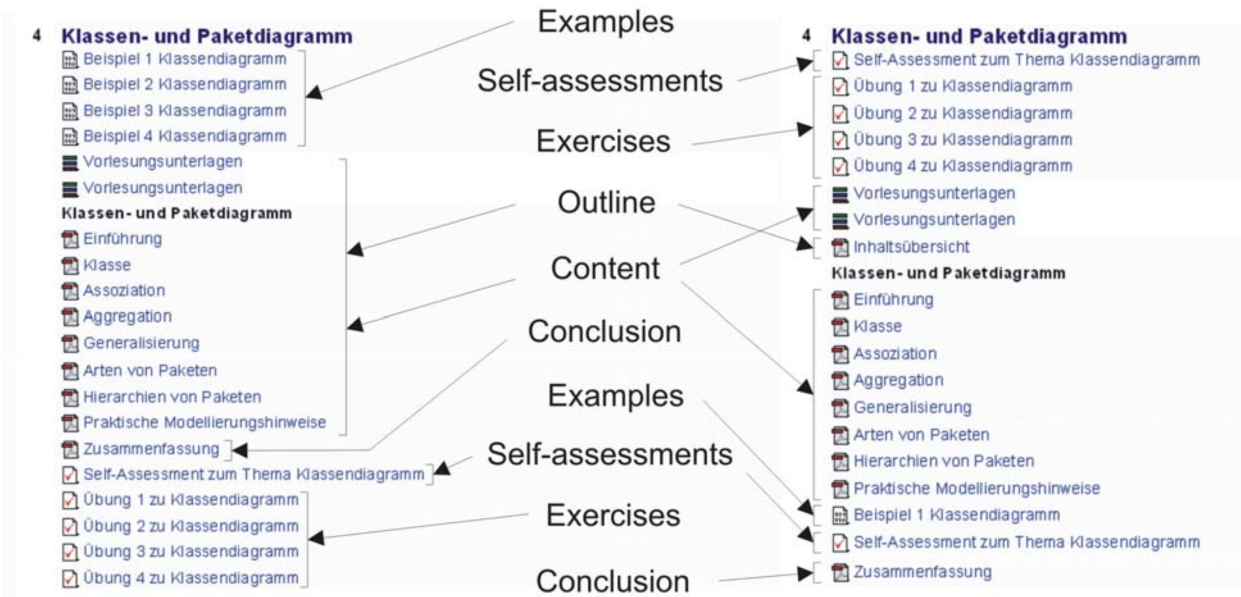

Figure 1: General structure of the course

According to FSLSM, active learners prefer to learn by trying things out and doing something actively. Therefore, the number of exercises is increased and self-assessment tests are presented at the beginning and at the end of a chapter. After the self-assessment tests and exercises at the end of the chapter, a final summary is provided in order to conclude the chapter. Moreover, active learners tend to be less interested in examples, since examples show how others have done something rather than let them doing it themselves. Therefore, a small number of examples are presented for active learners. Since outlines do not emphasise active learning, outlines are only presented once before the content objects rather than additionally between the topics. In contrast, reflective learners prefer to learn by reflecting on the leaning material and thinking things through. Therefore, the number of elements asking for active behaviour (such as exercises and self-assessment tests) should decrease. Furthermore, it is recommended presenting first the learning material in terms of content objects so that learners can reflect on it and afterwards showing examples or asking them to do some tasks based on the learned material. Moreover, we provide outlines additionally between the topics and a conclusion straight after all content objects in order to facilitate the learners to reflect about the already learned material.

Sensing learners prefer to learn concrete material such as data and facts. They also prefer to learn from examples. Therefore, the number of examples should increase for sensing learners and examples should be presented before the abstract learning material. Since sensing learners also like practical problem solving, the number of exercises should increase. Moreover, it is known that sensing learners prefer to solve such problems by already learned approaches. Therefore, we recommend providing tasks such as exercises and self-assessment tests only after the learning material. On the other hand, intuitive learners like challenges and therefore tasks like self-assessment tests and exercises can be presented before the learning material. Since intuitive learners prefer to learn abstract material and do not like repetitions, the presentation of outlines between topics should be avoided and the number of examples and exercises should decrease. However, in contrast to sensing learners, examples should be presented after the abstract content.

Since sequential learners prefer to learn in linear steps with a linear increase of complexity, we recommend presenting first the learning material, then some examples, and afterwards a self-assessment test and some exercises. Since sequential learners are more interested in a predefined sequential learning path than in getting the overview of the course, outlines are presented only before the content objects. In contrast, for global learners it is very important to get the big picture of the course. This can be supported by providing outlines additionally between the topics, presenting a conclusion straight after the content, and providing a high number of examples after the learning material. Furthermore, global learners tend to be poor in using partial knowledge. Therefore, the presentation of examples, exercises, and tests should be avoided at the beginning of a chapter and supported at the end of a chapter where the learners already have a better overview about the learned material.

Based on the above description of how to suit courses to specific learning style preferences (active, reflective, sensing, intuitive, sequential, and global), a value is determined for each adaptation feature and each learning style preference. These values indicate whether the specific adaptation feature supports a specific learning style preference (+1), should it be avoided in order to support the learning style preference (-1), or that it does not have an effect for the learning styles preference (0). Based on the actual learning styles of the students (e.g. active, sensing, and global), the respective values are summed up, using the strength of the preference as weight, distinguishing between a strong (2), moderate (1), and balanced (0) preference. The result indicates whether a specific course element should be presented at a specific position (for features about outline, conclusion, and self-assessment tests) or respectively how many of these elements should be presented (for features about examples and exercises). This approach is necessary due to possible ambiguous preferences between different dimensions of the FSLSM.

Add-on for Extending Moodle

Moodle (2007) is an often used and widely distributed open source learning management system (LMS), which provides a variety of features to create and manage online courses. Moodle was chosen for our experiment based on a preceding evaluation of open source LMS (Graf & List 2005). According to this evaluation, Moodle achieved the best results regarding the overall functionality as well as the adaptation issues and therefore was considered as the most suitable LMS for extending to an adaptive one.

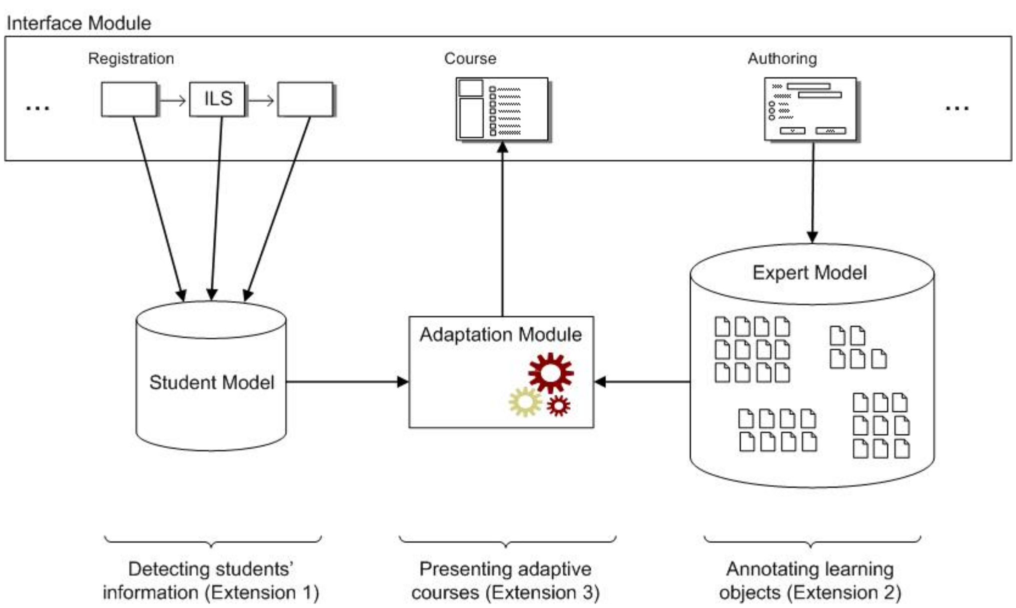

Figure 2: Extensions of the LMS architecture

We developed an add-on to Moodle that enables the LMS to provide adaptive courses based on the learning styles of the students. Figure 2 shows the implemented extensions of the add-on in the architecture of the LMS. First, meta-data were included in order to distinguish between the required course elements. In Moodle, the module quiz can be used to present exercises and self-assessment tests and the module resource can be used to present content objects, outlines, conclusions, and examples. As an extension, we added a field in the authoring interface for creating quizzes and resources in order to distinguish between the course elements. These meta-data are then passed to the expert model. The second extension deals with detecting and storing the learning styles of the students. For detecting learning styles, we used the Index of Learning Styles (ILS), a 44-item questionnaire developed by Felder and Soloman (1997). We added the ILS questionnaire to the registration form in Moodle, enabling us to calculate the resulting learning style preferences from the students' answers, and stored the preferences in the student model. As suggested by literature (Felder & Spurlin 2005), we distinguished the preferences only as strong, moderate and balance (e.g. strong active, moderate active, balanced, moderate reflective, and strong reflective preference) rather than values between +11 to -11 for each dimension. The third extension enables the system to automatically provide courses that fit to the learning styles of the students. Therefore, the adaptation module was developed, which is responsible for accessing the information about students' learning styles through the student model and calculating the values of each adaptation feature based on the students' learning styles preferences. The values of the adaptation features indicate how the individual course should be composed. Then, the suitable course elements are accessed through the expert model and presented to the students via the interface in the LMS.

Evaluation

In order to evaluate the effectiveness of the provided adaptivity, the adaptive version of Moodle was used for a course at Vienna University of Technology by 437 students. In the following subsections, we describe the experiment design, the method of statistical analyses, and the results of the performed analyses.

Experiment Design

The experiment is based on data from an object oriented modelling course which was taught at Vienna University of Technology, Austria, in winter term 2006/2007. The course consists of a lecture and a practical part, where students had to submit 5 assignments. The whole course was managed via Moodle, including the introduced add-on for providing adaptivity. The aim of using a LMS was to provide students with additional learning material and learning opportunities in order to facilitate learning.

The online course consisted of 7 chapters. Five chapters dealt about the main concepts of object oriented modelling, where each concept was introduced in one chapter. Furthermore, an introduction chapter and a chapter about the practical use of object oriented modelling were provided. Due to the focus on the chapters about concepts, only for these five chapters adaptivity was provided. Overall, the course included 424 content objects. Moreover, each chapter included one or two files providing all content objects as print-version. For all chapters, an outline, a conclusion, and a self-assessment test was available. Overall, the seven self-assessment tests included 114 questions. For each of the 5 chapters that were adapted, additionally 5 examples and 5 exercises exist. The exercise included overall 181 questions. The two chapters which were excluded from adaptivity did not include examples and exercises. Furthermore, a forum was provided for the course. To examine the knowledge of the students, 5 marked assignments were included within the 7 chapters, where each assignment dealt with one or two chapters. The assignments had to be done in groups of two. Few days after the submission, each student had to present the solution individually and had to answer questions about it. At the end of the course, each student had to pass a written exam. Although parts of the assignments were done in groups of two, the course was designed in a way that all students needed to learn everything and they were examined on all topics; hence the course was appropriate for investigation of individual learning.

When students registered in Moodle, they were asked to fill out the ILS questionnaire. Afterwards, they were assigned randomly to one of the three groups: students belonging to the first group were presented a course that matched with their learning styles (referred to as matched group), the second group got a course that mismatched with their learning styles (referred to as mismatched group), and the third group got a course where all available learning objects were presented in a default sequence independent of the students' learning styles (referred to as standard group). Students belong to their assigned groups for the whole course. When the students logged in to the course, Moodle automatically presented the course according to the assigned group and the students' learning styles respectively. However, the presented course acted as a recommendation. Independent of the assigned group, students had the possibility to access all learning objects via a link at the overview page of the course.

Method of Statistic Data Analysis

Data of students who spent less than 5 minutes on the ILS questionnaire were discarded because the detected learning styles were considered as not reliable enough. Also, we included only data from students who submitted at least 3 assignments which was a requirement for a positive mark. Therefore, data of 235 students were finally used for analyses, whereby 79 students belonged to the matched group, 78 to the mismatched group, and 78 to the standard group.

The aim of the analysis was to show differences over the three groups. Therefore, we investigated the students' performance and behaviour in the course. Regarding the performance, we looked at the average score on the assignments (ranged from 0 – 50). We used the average score rather than the total score, since the requirements for a positive grade was to submit at least 3 assignments and have more than 50% of the scores. Therefore, some students left out the last assignments when they had enough scores for a positive mark. Since the focus of our analysis is on the effect of learning rather than on the final marking, we considered the average mark as more reliable. Additionally, the analysis includes the score on the final exam. Regarding the behaviour in the LMS, we looked at the time students spent in the course, the number of logins into the learning environment, and the number of performed learning activities. For the time, we set thresholds in order to avoid the inclusion of learning breaks. We considered a maximum time span of 20 minutes for examples and exercises and for all other learning objects a maximum time span of 10 minutes. Furthermore, we included only the time spent on learning activities rather than considering also administrational activities. For the behaviour in the course, we used the total number and amount of time rather than the average over the performed assignments. The reason is that students had to learn all chapters in order to pass the final exam, regardless of whether they had submitted all assignments. Furthermore, we investigated how often learners left the recommended learning path and asked for not recommended learning objects.

For analysing differences between the three groups, we used group comparison methods for each variable (e.g. time, number of logins, and so on). Outliers were excluded for each group and variable. Two tailed t-test was applied for the variables where data was normal distributed and two tailed Mann-Whitney U test (u-test) for variables where data was not normal distributed. To check whether data was normal distributed, we used Kolmogorov-Smirnov test.

Results and Discussion

The results of the performed tests can be seen in Table 1. Significant results are highlighted in bold font. The T and U values as well as whether t-test or u-test was conducted, and the significance levels (p) is presented.

		Matched & Mis-matched Group		Matched & Standard Group		Mismatched & Standard Group	
Variable	t-test/ u-test	T or U	P	T or U	p	T or U	p
Time spent on learning activities	U	**1927**	**0.014**	**1960**	**0.020**	3014	0.921
Number of logins	T	-1.819	0.071	**-2.659**	**0.009**	-0.684	0.495
Number of visited learning activities	U	2517	0.327	2513	0.466	2684	0.837
Average score on assignments	T	-0.245	0.807	-1.569	0.119	-1.377	0.171
Score on final exam	T	-1.443	0.152	-1.336	0.184	0.228	0.82
Number of requests for additional LOs	T	**-2.093**	**0.038**	-0.474	0.636	1.819	0.071

Table 1: Results of the comparison between groups

As can be seen from the results, a significant difference was found with respect to the time students spent on learning activities in the course for the matched and mismatched group as well as for the matched and standard group. According to the results, students belonging to the matched group spent significantly less time in the course than students from the mismatched and standard group. The same tendency can be seen for the number of logins. Students belonging to the matched group logged in significantly less than students belonging to the standard group. Regarding the number of visited learning activities, no significant difference could be found. This might be due to the fact that visiting a higher number of learning objects does not necessarily indicate that the students learned more. Other parameters such as low working memory capacity or an active and/or global learning preference might be the reason for students to go back more often to already visited learning objects or to prefer to explore the learning environment by looking around and clicking at different learning objects before starting to actually learn the content. Therefore, this variable needs further analysis in order to find out whether it is in agreement with the other two variables regarding the students' behaviour. Regarding the performance of students in terms of scores, significant differences between the groups were found neither for the assignments nor for the final exam.

Based on the results, we can conclude that students from the matched group spent less time in the course but achieved on average the same scores as the students in the mismatched and the standard group. This is in agreement with our expectations, since learners from the mismatched group were presented a course that did not match with their learning styles but they had the possibility to access all available learning objects. According to the results of comparing the number of requests for additional, not recommended learning objects, it can be seen that students from the mismatched group asked significantly more often for additional learning objects than learners from the matched group. Therefore, it seems that students belonging to the matched group were satisfied with the recommended course, whereas learners from the mismatched group were more often looking for additional learning objects. Students belonging to the standard group did not show a significant difference either to the matched or to the mismatched group. Looking at the total number of requests for additional learning objects, students from the standard course seem to be less satisfied with the course than the matched group and more satisfied than the mismatched group, which again confirms the effectiveness of providing course that fits to the learning styles of students.

Conclusion and Future Work

In this paper, we demonstrated how learning management systems can be enabled to provide adaptivity based on learning styles. We introduced a general concept for LMS to automatically generate courses that fit to the learning styles of the students. The only additional effort for the authors and course developers is to provide some meta-data in order to annotate the learning material. Furthermore, students were asked to fill out the ILS questionnaire for detecting their learning styles. The concept was implemented as add-on to Moodle and an experiment with 437 students was performed to show the effectiveness of the concept and the developed add-on. The results show that students who were presented a course that matched with their learning styles spent significantly less time in the course but achieved on average the same marks as those students who were presented a course that did not match with their learning styles and students who were presented a standard course with all available learning objects. These results show that providing courses in LMS that fits to the learning styles of students helped the students to learn more effectively and therefore facilitated better learning for them.

Only few studies, for instance, the study by Bajraktarevic, Hall, and Fullick (2003) and by Brown et al. (2006) have investigated the effect of adaptivity based on FSLSM with respect to students' performance and/or behaviour. While these studies focused on only one dimension of FSLSM, we developed a new concept for considering different dimensions of FSLSM. This allows providing more accurate adaptivity by incorporating different aspects of learning styles as proposed by the learning style theory. Furthermore, although our approach recommends students a certain course, they do have the opportunity to leave the recommended learning path and access all available learning objects. Moreover, our approach is based on LMS rather than on adaptive systems. By enhancing LMS with adaptivity, teachers can continue holding their courses in LMS and therefore taking all advantages of LMS.

Future work will deal with an in-depth analysis of the results with respect to different learning style dimensions as well as the different adaptation features. We also plan to add more adaptation features to our concept and implement them. Another future direction will be to combine the proposed concept with an automatic student modelling approach so that the system is able to automatically detect the learning styles of the students based on their behaviour and actions in the LMS.

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