Developing an Author's Request Manager of Style-Based E-Learning

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Abstract — *Educated and skilled human resources and workers are real assets and a key of success and power for both nations and organizations. Therefore, education and training in general, and Web-based Intelligent Tutoring Systems (ITS) in specific will expectedly play an important role in the future.*

This paper aims at supporting teachers in properly authoring their courses and in selecting the appropriate course material required to meet specific course objectives for a specific student or group of students knowing their exact knowledge and cognition model (learning style). Knowing the specific model for an individual student during course delivery allows adapting the learning material for more effective learning.

A prototype environment is developed to help instructors in creating and maintaining Learning Object (LO) repositories and to deliver the course material to the students adaptively according to their individual student models. Live experiments for evaluation were also conducted. The results proved that both the efficiency and effectiveness of the learning process have been recognizably improved.

Key Words — learning style, Learning Object, e-learning, SCORM and Student Model.

I. INTRODUCTION

E-learning is playing an important role as a primary learning mechanism. In fact, E-Learning is considered a paradigm shift in education systems as it turns teaching into learning, i.e., promoting learning experiences instead of teaching.

A key to effective automated learning systems is the ability to adapt learning strategies to the needs of individual students. Intelligent Training Systems (ITSs), such as The Smart Tutor [1], IDEAL [2], and DANDIE [3], dynamically adapt the course strategy for each individual student based on his profile and model. Other systems [4] used the student model to group students into consistent groups according to their learning progress. This aids teachers to decide on the suitable supplementary material and/or lessons for the whole group.

Student Model (ST) captures information about the student knowledge, and learning profile. The importance of student

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modeling and its role in the education process has been recognized since mid 80's, and hence it had attracted researchers since then. Rambally [5] in 1986 have presented one of the early attempts for student modeling. A naive model is presented. It related the experts' knowledge and the student knowledge of a particular domain and expressed them in terms of equivalence classes that partition the domain. The comparison between both partitions is used to ascertain what the student knows, his misconceptions, and his learning abilities. In IDEAL [2], a student model is inferred from the performance data using a Baysian belief network. The measure of how a skill is learned is represented as a probability distribution over competence levels, such as novice, beginning, intermediate, advanced, and expert. To simplify the algorithm, questions of similar difficulties are grouped into categories associated with the conditional probabilities of answering each set of questions correctly to the possible skill level. The probabilities are further reduced by matching the question categories to the competence levels. Circsim-Tutor [6] models the student in terms of four components: performance model, student reply history, student solution record, and tutoring history model. The student evaluation is divided into four levels that correspond to the four stages of solving the problems chosen for evaluation: global assessment, procedure-level assessment, stage assessment, and local assessment. The local assessment is updated after each tutoring interaction; all other assessments are calculated from the local assessment. The assessment model is based on a set of simple heuristics, e.g., the local assessment depends on fifteen different patterns found in the student's answers.

Several student-modeling researches use fuzzy logic to accommodate the uncertainty in the evaluation procedure. The ML-Modeler [7] utilized the fuzzy probability distributions in association with knowledge variables to avoid the complexity of Bayesian probabilities. It represented the FPD as a 7-tuple with the first element represents the least probable end of the FPD and the 7th element representing the most probable. Magoulas et al. [8] used a three-stage approach that is realized by a set of connectionist networks. The first stage of each network fuzzifies inputs that contribute to the evaluation of the level of understanding, based on the estimations of experts to the degree of association between an observed input value and the learner's knowledge of the concept, and hence, a fuzzy subset is generated for each measurement or answer. The next stage realizes a fixed weight aggregation network that processes these fuzzy subsets. A preliminary decision is expressed by a fuzzy subset relating an answer to the possible qualitative characterizations