Journal of Network and Computer Applications 36 (2013) 533–542

Contents lists available at SciVerse ScienceDirect

Journal of Network and Computer Applications

journal homepage: www.elsevier.com/locate/jnca

A personalized e-course composition based on a genetic algorithm with forcing legality in an adaptive learning system

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ARTICLE INFO

Article history:
Received 2 August 2011
Received in revised form
9 February 2012
Accepted 3 April 2012
Available online 25 May 2012

Keywords:
Adaptive learning
Personalized learning
Artificial intelligence
Evolutionary algorithms
Genetic algorithm
Particle swarm optimization

ABSTRACT

This paper proposes a personalized e-course composition based on a genetic algorithm with forcing legality (called GA*) in adaptive learning systems, which efficiently and accurately finds appropriate e-learning materials in the database for individual learners. The forcing legality operation not only reduces the search space size and increases search efficiency but also is more explicit in finding the best e-course composition in a legal solution space. In serial experiments, the forcing legality operation is applied in Chu et al.'s the particle swarm optimization (called PSO*) and Dheeban et al.'s the improved particle swarm optimization (called RPSO*) to show the forcing legality can speed up the computational time and reduce the computational complexity of algorithm. Furthermore, GA* regardless of the number of students or the number of materials in the database, to compose a personalized e-course within a limited time is much more efficient and accurate than PSO* and RPSO*. For the experiment increasing the number of students to 1200, the average improvement ratios of errors (learning concept error, materials difficulty error, learning time error), fitness value, stability, and execution time are above 96%, 79%, 90%, and 10%, respectively. For the experiment increasing the number of materials to 500 and the execution time set to the shortest execution time of RPSO*, the average improvement ratios of errors (learning concept error, materials difficulty error, learning time error), fitness value, and stability are above 97%, 51%, and 80%, respectively. Therefore, GA* is able to enhance the quality of personalized e-course compositions in adaptive learning environments.

1. Introduction

With the rapid development of the Internet, e-learning applications are widely becoming used (Chang and Chen, 2009; Chang et al., 2011, 2009a,b; Charsky and Ressler, 2011; Hsieh et al., 2011; Huang et al., 2011; Hwang et al., 2011; Wang, 2011). Students can learn new knowledge through the Internet regardless of time, location, or other restrictions. Although many e-learning systems can provide a wealth of teaching materials and a variety of functions, most systems cannot provide adaptive materials according to the student's ability. Therefore, how to provide an adaptive learning environment has been an important issue for instructors. Personalized adaptive learning is intended to provide learning materials which meet the needs of individual learners (Brusilovsky, 1999; Brusilovsky et al., 1998; Chen et al., 2005; Chu et al., 2011; Lee, 2001; Liu and Yang, 2005). To integrate diverse learning resources, there are many intelligent tutoring systems (Learning Resource Meta-data Information Model Version 1.2.2, 2004; Reload Tool, 2004; Yang et al., 2004) based on learners' characteristics and differences to provide appropriate materials and teaching strategies. According to researches (Brusilovsky, 1999; Brusilovsky and Maybury, 2002; Huang et al., 2007; Lee, 2001; Liu and Yang, 2005), adaptive learning is able to improve a learner's learning efficiency and effectiveness.

However, Linderoth and Savelsbergh (1999) conducted a comprehensive computational study demonstrating that the mixed integer programming problems are NP hard (Non-deterministic Polynomial-time hard), which implies that composing optimal personalized e-courses from a large database is computationally prohibitive. To cope with this difficulty, evolutionary algorithms have widely been used for finding near optimal solutions in NP-hard problems, which have no deterministic polynomial time algorithms for finding the optimal solution (Tang et al., 2010). Hence, evolutionary algorithms are proposed to find quality approximate solutions with a reasonable time, which are useful in effectively achieving the requirements of adaptive e-learning environments in artificial intelligence techniques. To achieve adaptive e-learning environments, the adaptive materials which are selected by these evolutionary algorithms should simultaneously meet multiple criteria.

For the above reasons, many studies based on artificial intelligence techniques have been developed to achieve personalized learning environments. To provide more interactive and cooperative characteristics in the learning process for individual

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http://dx.doi.org/10.1016/j.jnca.2012.04.002

learner, Huang et al. (2008) proposed an e-learning system based on PSO (Particle Swarm Optimization) to automatically compose auxiliary materials from serial blog articles, which satisfies multiple assessment requirements such as the number of blog comments, the difficulty level of blog articles, the expected ratio of unit topics, and the amount of trackbacks along with each blog article. Teachers, learners, or course designers may post blog articles to offer assistance or add a discussion and through PSO draw the selected blog articles to generate RSS (Really Simple Syndication) feeds. Next the system takes these RSS feeds to sort the auxiliary materials ordered according to the related topics within a course. By these RSS feeds, learners can collect their own needed auxiliary materials and external information; furthermore, they are able to subscribe to the RSS feeds directly to obtain the auxiliary materials. Huang et al. (2007) used GA (Genetic Algorithm) to construct a learning path for individual learners. Chang et al. (2009b) combined *k*-nearest neighbor classification and GA to identify students' learning styles in e-learning systems. Hwang et al. (2008) proposed an e-learning system using GA to automatically reply question answers for students.

Furthermore, the test construction problem is a combinational optimal problem, and there is also no polynomial time algorithm that exists for finding the optional solution. Many evolutionary algorithms are used for test combinations (Hwang et al., 2006; Huang et al., 2009; Lee et al., 2007; Wang et al., 2009). Cheng et al. (2009) used a PSO algorithm to select tailored questions for each learner from a large-scale item bank and simultaneously satisfy multiple assessment requirements, such as the exposure frequency of questions, the relevant topics of the current examination, the weight of each topic, and the difficulty level of a test item. Yin et al. (2006) used a PSO algorithm to improve the efficiency of composing optimal serial test sheets from a large item bank, which can be used to evaluate student learning status. Recently, Chang and Shiu (to appear) proposed an adapted CLONALG algorithm for simultaneously constructed IRT-based (Item Response Theory) parallel tests from a large item bank. The above studies are aimed at developing personalized learning or test combinations based on artificial intelligence techniques in e-learning environments. In other words, the problems of e-course composition to achieve personalized learning or test construction in e-learning environments are combinatorial optimization problems.

Many studies (Huang et al., 2007, 2008; Hwang et al., 2008; Lee, 2001; Liu and Yang, 2005; Yin et al., 2006) consider various factors to achieve personalized e-course compositions. After observing the consideration factors for achieving personalized learning environments, they should involve the following: (1) the difficulty of e-learning material, (2) the learning concepts of the e-learning material, (3) the required time for reading e-learning material, (4) the learner's expected learning time, and (5) the ability level of the learner. According to these factors, Chu et al. (2011) proposed a personalized e-course composition approach based on PSO to compose appropriate e-learning materials into a personalized e-course for individual learners. As previously stated, the personalized e-course composition to achieve personalized learning is a combinational optimal problem. For learners, the composed e-learning materials can provide a truly personalized learning environment; instructors who want to achieve a personalized learning environment for students can save much time and effort. Chu et al. indicated that the computation complexity of PSO will be increased in the following situations: (1) the number of e-learning materials is increased and (2) the particle number in PSO is increased. However, if the number of e-learning materials is increased, a larger number of particles should be applied to find the most suitable personalized e-course. This situation certainly increased the computation complexity of PSO. According to the experimental results, the stability and execution time of PSO are much lower than those of GA and random approach.

Dheeban et al. (2010) proposed a modified PSO algorithm (MPSO) with inertia coefficient (Kennedy and Eberhart, 1995, 1997) to improve the solution characteristics in Chu et al.'s scheme. There are two models in MPSO: linear varying inertia coefficient PSO (LPSO) and random varying inertia coefficient PSO (RPSO). The experimental results show that the fitness values of LPSO and RPSO are smaller than PSO in Chu et al.'s approach when the number of learning materials increases. They considered that the number of learning materials will grow in the future. In Dheeban et al.'s experiment, the fitness value of RPSO is smallest when the number of materials is 185 and the iteration is larger than 640. RPSO is more suitable than LPSO for a large number of materials. For the same situations as ours, Chu et al.'s PSO and Dheeban et al.'s RPSO are compared with our proposed algorithm.

As it is well known, with the popularization of the Internet, the demand for e-learning has greatly increased. An e-learning environment provides another learning channel that enables learners to break through the limitations of time and space. One of the important advantages of e-learning is adaptive learning environments, in which the provision of learning content can meet individual students' demands. However, it not only takes a great deal of time and effort for instructors to search for appropriate e-learning materials from a database, but these materials which are selected should simultaneously meet many consideration factors. Many students do individual learning via a web-based adaptive learning system anytime and anywhere. Therefore, the greater numbers of e-learning materials the more students will participate in such an e-learning environment. Obviously, the computation complexity of the algorithm will be increased and more time should be taken to find the best adaptive e-learning materials composition. Unfortunately, both the PSO algorithm applied in Chu et al. (2011) and MPSO algorithm applied in Dheeban et al. (2010) did not consider the fact that the number of students would increase over time. They did not analyze the situation of increasing students in their experiment. That is, the system should consider scalability to satisfy the explosive growth of students in e-learning environments. Furthermore, Chu et al. compared the different number of particles in PSO to compose a personalized e-course, showing that PSO with a large amount of particle numbers generates a personalized e-course combination that corresponds to the characteristics of learners better than PSO with a small amount of particle numbers. Although this situation generates a personalized e-course combination that corresponds to the characteristics of the learners, more time is needed to compose personalized e-courses than the PSO with a small amount of particle numbers. On the other hand, in fact, instructors come from various areas and are not always familiar with setting and adjusting the most suitable particle numbers. This results in the quality of personalized e-courses derived by PSO being unstable. Overall, Chu et al. and Dheeban et al.'s system does not satisfy the explosive growth of students in e-learning environments since PSO is not efficient when there are a large number of students in the system.

Above all, this paper proposes a personalized e-course composition based on GA with the "forcing legality" concept, which is called GA* in an adaptive learning system. Unlike the original GA analyzed in Chu et al.'s paper, GA* controls each chromosome so that it consists of a feasible combination to enhance its search capability. Some materials in the database will possibly produce an excessive burden for each learner. Therefore, GA* rules out inappropriate e-learning materials for the learner in the database to reduce the search space and the computation complexity of the algorithm. At the same time, our system considers the aforementioned factors to constitute an adaptive e-course in a limited time. In the further experiments, PSO in