Introduction of teaching strategies as a method to increase effectiveness of knowledge acquisition

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ABSTRACT

The paper is devoted to teaching effectiveness in distant learning systems, and primarily focused on teaching strategies that support learning process. Developed algorithms, examine possible learning paths and align pace of knowledge absorption to student's personal (or student's groups) skills. Aforementioned strategies implement automatic assignment of learning difficulty factor based on individual student’s characteristics.

Key Words: e-learning, learning process management, e-systems, computer aided learning

1. Introduction

E-learning is a type of technology supported education/learning where the medium of instruction is through computer technology, particularly involving digital technologies. E-learning has been defined as "pedagogy empowered by a digital technology" [11]. This domain of science is still not mature and suffers from lack of homogeneous and coherent vision how to put into practice remote teaching process. In the majority of real-world cases, theory does not match practice, and this is the case with distance learning too. In e-learning systems, all efforts are usually technology driven in spite of the teaching theory driven, which in most cases badly influence effectiveness of the learning process.

Effectiveness of knowledge acquisition is a function of different forms, methods and variety of teaching methods [7]. Nowadays, in a computerization era teaching effectiveness in e-systems, may only increase, once appropriate steps are undertaken along with an application of classical forms and methods teaching, leading to a construction of suitable teaching structures, which are integrated with latest technologies and formal ways of presentation [10].

Teaching technology [9] is an interdisciplinary learning about education efficiency, pursuing for the answer for the question, how to educate quicker, faster, better and less expensive in a defined conditions.

Interdisciplinary nature of the technology relies on that, it draws its subject of the interest and research methods other disciples like computer science, cybernetics, theory of systems and communication theories.

In traditional method learning, human factor is responsible for entire teaching process [2, 6, 9]. This may lead to situations (and usually does), like loss of control over learning progress (due to e.g. mental fatigue of a teacher, badly adapted teaching materials to the students’ skills), which finally results in loss of student’s attention and willingness to learn. Nonetheless, excluding completely “human factor” is not possible and at the same time from a teaching perspective very disadvantageous factor [11, 12, 13], and it is tightly connected with students feeling of being alienated and loss of the control.

Remedy for aforementioned inconveniences might be application of an intelligent teaching system [1, 3, 4, 5, 8] that may increase effectiveness of knowledge acquisition.

2. Teaching strategies

Teaching strategies are algorithms that support navigation within a learning path, during knowledge acquisition process. These algorithms are responsible for directing students on the suitable difficulty variants in the nodes of the learning path. Appropriate assignment made by the strategies is being made in a way that teaching material is being selected to suit more than adequately[1] student's expertise level, and what is more his ability to learn, according to the criteria, which are discussed later on, in the chapter 4.

Navigation algorithms have to lead a student or a group of students thru learning path from first node (starting phase), to another, until end of learning path is reached. State after starting phase is named adaptive state (phase) and it lasts to the end of knowledge acquisition process.

Teaching algorithm operation is based on learning adaptation mechanisms[2], where knowledge absorption process is being scrutinized on the fly, and historical data, about lessons learnt and scores achieved, are being taken into account in order to assign right learning material in a next node from the learning path to achieve best possible (optimal) material acquisition.

Main task for an adaptive algorithm is to assign each student from a group, appropriate lesson difficult variant (in current *j* lesson), in order to achieve best result (*note*) in a competence test after the lesson. Best result means required /set one by the teacher at the beginning of learning process, usually it is a combination of notes and credit points, received upon lesson completion on a certain difficulty level.

Additionally, one should pay special attention to verify student's initial expertise level, to assign base difficulty factor for start lesson node (starting phase) to match student capability to learn. If the initial expertise is not detected well, it will affect learning efficiency later on, during learning progress (adaptive phase). During the adaptive phase, one of available learning strategies, is being assigned to a student, based on his initial expertise level so when an inaccurate strategy is chosen, it greatly affects learning progress and its effectives.

3. Validation of learning progress

Verification of knowledge acquisition during course duration takes place after each lesson, in a competence test. It is essential, in order to go to next lesson to firstly pass base current lesson difficulty variant (easiest one) in a node. Each student is assessed in a competence test and *note* is being assigned $\{\overline{0,1}\}$ that defines knowledge absorption factor for a lesson. Greater value from a $\{\overline{0,1}\}$ set scored more points student received in the competence test. Note's value that qualifies student to pass to next lesson is strictly dependent on his base expertise level and lesson's difficulty factor, which defines also current competence test.

Knowledge acquisition validation is being done for both a student and for a group (all its participants), after each lesson passed in a learning path (within competence test).

Validation procedure has to substantiate (according to taken assumptions), that in fact, strategies of learning adaption influence on improved[3] knowledge acquisition during learning phase.

The *notes* received are input data. Notes are taken from student's records, received in previously passed competence tests (along with a sum of credit points[4]) which constitute a base for the final assessment of learning progress quality.

In order to be eligible to pass to a next lesson, student must, at least, pass thru

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[1] Lesson difficulty factor is correlated with student's ability to comprehend given material.

[2] Learning adaptation means drawing conclusions out gathered historical data, and then based on them learning "parameters" tuning to match optimal learning pace and form for a student.

[3] One should think about improvement in terms of fulfillment of main, optimal learning, criterion which strives to constant student's grades increase, and the same instill as much knowledge as possible for every course participant.

[4] Credit point is received after each lesson, more credits earned if lesson is finished on a higher difficulty factor

easiest material variant in a current lesson node (current competence test must be completed with an acceptable note value) and receiving, at least, one credit point.

4. Learning process effectiveness

One of the most common problems in e-learning is lower than expected effectiveness of knowledge absorption. Author, it this paper focused mainly on the issue. Author concentrated on increasing learning effectiveness by teaching strategies introduction. It comes down to best teaching algorithm assignment either for a student or a group from a set of possible adaptive learning strategies. Each strategy ought to meet to given down below criteria.

These strategies ought to organize learning process in way that best suits student's abilities to learn and finally improves the grades (and credits) received.

Main criterion, taken into consideration during assessment of learning effectiveness improvement process, is striving after receiving best possible grades and at the same time more credits.

These are two opposing criteria. Receiving best grades could be achieved in an easy way by assignment in every node easiest difficulty variant, however it would result in receiving less credits than expected afterwards. Receiving greatest number of credit is only possible once the most difficult lesson variants are being assigned and finished in the node. Aforementioned facts allow us to clearly asses the quality of teaching strategies.

Other characteristics that prove usefulness of a particular strategy are: a total number of students (from a test group) that received at least a half possible credit points during entire learning process. Grades average in a learning process is a supporting factor.

Strategies also strive after fulfilling given below assumptions:

- minimize number of students that cannot comply the optimal learning postulate (minimize drop out from learning process – do not complete competence tests on a required level)
- detect students with incorrectly detected initial expertise level (especially in a start phase)
- "exploit" best students – to assign them more difficult lesson's variants

As criteria for starting phase strategies quality assessment following have been taken into account:

- Percentage of students that have received more than half credits possible, number of grades scored above group's average, group grade's average, lowest and highest student grade's average

As criteria for adaptive phase strategies quality assessment following have been taken into account:

- expertise level distribution changes in time (compare before and after learning), sum of credits after learning process is over, student/group grade's average, number of students that finished learning with more than half possible credits to earn

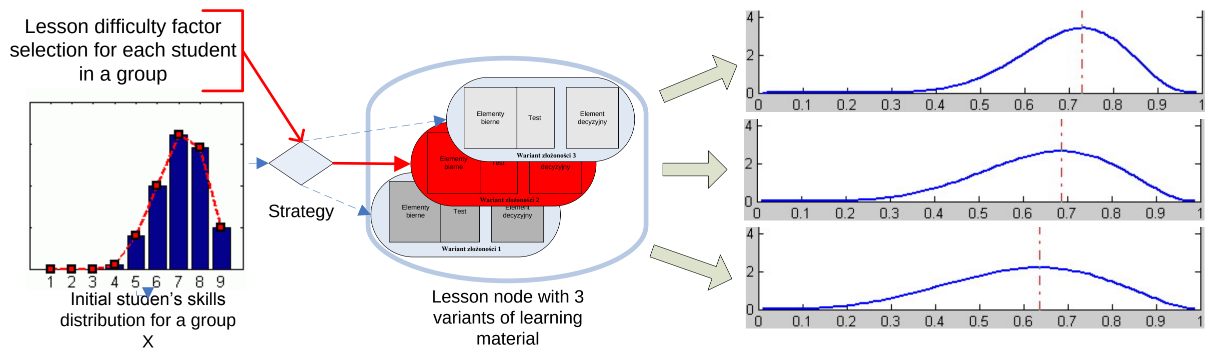

Fig. 1. Lesson's difficulty variant selection – based on navigation strategy

Each strategy, should meet at least one of aforementioned (main) criteria. Besides each strategy have its own characteristics e.g. global optimum strategy strives to find strategies should be able to find students that are more talented[5] (once found – they are being assigned more difficult / challenging task / lessons). Each strategy acts in a different way based on a student profile detected during learning process. For example minimalistic strategy, strives after assignment students easiest possible lesson's variant in a learning path.

5.Results

Starting phase. All the students from the test groups were treated by the start phase strategies, and the experiment data were evaluated against optimal teaching criteria postulate – namely striving after receiving top grades with most possible credits earned and to match difficulty factor with student's expertise level.

Primitive strategy did not prove its usefulness, failing to match second part of requirements (differentiate students base on their expertise level). This strategy was not intended to be applied ever, in any system, and the results received after primitive strategy application, constituted a base for comparison. *Random* strategy, in spite of the fact that partially[6] met the requirements, gave good results (mainly in the group where most of the students were good learners – no matter what lesson's difficulty they were faced to they were able to cope with).

Proportional lesson difficulty variant assignment done by a proportional third strategy turned to be most efficient (against each test group), both in terms of average grades scored and credits earned. Thanks to it, more than 60% of students received better scores than expected.

Adaptive phase. Best strategy assessed in this phase should meet criteria described in chapter 4. In order to quickly sum up discussion of received results, if the priority was to get most students that passed learning path with higher than a group credit points average number, one should focus on Reference strategy or Optimal one. Focusing only average of grades maximization the most suitable are reference *conservative* and *reference* ones. Most balanced strategy that matches all criteria is *optimal* strategy. It equally good strives after grades and credits scored during entire learning path.

[5] Talented means student who scores grades higher than model student

[6] Partially - since only some of the students were assigned lesson's difficulty factors that match their expertise level.

6. Summary

Quick and unfortunately chaotic e-learning systems development created an urgent demand to adjust teaching process to the individual characteristics. Along with the growth of interests around distant learning, numerous systems are being implemented, yet again without orientation on a learner. The systems do not base on any student model or what is even worse do not adjust pace of learning to the student needs. This paper was intended to provide a solution to ease teaching material delivery, in an personalized way, that match student's expertise level. Based on a defined model of learner – system has to ascribe a teaching strategy that will facilitate knowledge acquisition during entire learning process. Tested, in two phases (start and adaptive) strategies allowed to increase learning effectiveness, portrayed by results (increased number of credit points and average of grades).

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Feature	**Strategy name:**		
	Random	*Proportional*	*Primitive*
Personal characteristic taken into account	No	Yes	No
Different navigation algorithms	No	Yes (3)	No
Lesson difficulty variant assignment based on student's expertise	No, random	Yes	No

Tab. 1 Start phase strategies – characteristics

Feature	**Strategy name:**			
	Optimal	*Conservative*	*Simplistic*	*Reference*
Diverse behavior based on student's expertise level	Yes	No	Partially	No
Talented students exploitation	Yes	No	Yes	Yes
Keep student on a lesson variant which was set initially	Yes	No	No	No
Student is able to repeat failed competence test along with lesson (how many times)	Yes, (x3)	Yes, (x3)	Yes, (x3)	Yes, (x3)
Memory effect	Yes	No	Yes	No
Korekcja różnic w poziomie wiedzy (rzeczywisty, a wyznaczony przed fazą wstępną)	Yes	No	Partially, just detection	Partially, just detection
Start phase impact	No	Yes, huge	Partial, small	Partial, small
Focus on: 1. lowest possible number of student that will quit from learning 2. average student in group 3. talented students 4. expertise level verification 5. maximization of results (defined as optimal learning conditions)	3, 1, 4	1, 2	1, 2	2, 4, 5

Tab. 2 Adaptation phase strategies - characteristics