IDD PERSONALIZING MODEL

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Abstract: This paper focuses on the efforts towards the development of an e-learning system that will personalize the learning experience of users by using an IDD method which is composed of Increment & Decrement reference (IDR) table and Difficulty level model. The paper starts with a brief description of e-learning systems and its diffusion in the present day educational system. The paper then concentrates on the design of an assessment module of the e-learning system, which is targeted to be its strength and advantage over other e-learning systems. Finally a conclusion with suggestions on how the system can be further enhanced for a more effective learning experience is presented.

Key-Words: E-Learning, IDD personalizing model, Increment & Decrement reference (IDR) table, Difficulty level model and fuzzy.

1 Introduction

Due to the overall popularity of the Internet, e-learning has become a hot method of learning in recent years. As adopted from [6], E-learning can be defined as a technology-based learning in which learning materials are delivered electronically to remote learners via a computer network. A more detailed definition can be described as the delivery of formal and informal training activities, processes, communities and events via the use of all electronic media like Internet, Intranet, Extranet, CD-ROM, video tape, DVD, TV, cell phones, personal digital assistant (PDA) etc. [4].Through the electronic devices such as the Internet, learners can freely absorb new knowledge without the restriction of time and place [5]. While, it is undeniable that a well designed e-learning system must always contain relevant, organized and structured materials, it is truly important also for a well designed e-learning system to provide awareness among the learner by adapting or reacting to each learner's learning needs and styles.

Dolog and Sintek [2] have also pointed out that it is important to personalize support for learners because e-learning takes place in open, dynamic learning and information networks. Derntl and Motschnig-Pitrik [1], have highlighted the fact that much research has been devoted to producing e-learning content, describing it with metadata and to constructing e-learning platforms. However, less attention has been paid to using technology to improve the learning process in terms of depth and scope.

An E-learning system should accommodate different learning styles and foster learning through a variety of activities that apply to different learning styles. Learners can learn at their preferred rate and also be able to select learning materials, or be directed to the content that meets their level of knowledge, interest and what they need to know to perform more effectively in their particular activity [3]. While research on the technical aspects of e-learning is active, the psychological aspects of e-learners cannot be neglected in order for e-learning to be a success. Our research is focused on providing a mechanism whereby an e-learning system can be personalized to cater for the individual student's learning ability and patterns. In the following section, an IDD personalizing model which has been designed to cater for each individual learner's personal learning pattern will be described.

2 Core concept of IDD Personalizing Model

An IDD Personalizing Model is a fuzzy evaluation model which composes of a value matching method between an IDR table and a Difficulty level model which is deployed in the design of a personalized learning assessment module.

Before constructing the IDD Personalizing Model, a test bank with questions which are categorized to three levels of difficulties (easy, moderate and tough) has been predefined by using survey method. Once the test questions have been labeled accordingly, an assortment of questions to the learners are founded based on the follow rules:

Rule 1: When a learner performs poorly in an assessment, the next time the learner retakes or goes for another assessment, the number of easy level's questions will be increased and the number of tough level's questions will be decreased.

Rule 2: When a student performs very well in an assessment, the next time the learner goes for another assessment, the number of tough level's questions will be increased and the number of easy level's questions will be decreased.

The above rules will imply the following conditions:

Condition 1: When the number of easy questions increases, the number of tough questions decreases accordingly and vice versa.

Condition 2: The number of easy questions is always non-proportional to the number of tough questions. The number of tough questions is always proportional to the increment of the difficulty level.

A generic difficulty level diagram was then deployed using the fuzzy model. A fuzzy set of question pool was defined according to three levels of difficulties which have been mentioned above. The purpose of having a difficulty level model is to classify and obtain the number of easy, moderate and tough questions that are randomly generated from the question bank to be set in an assessment. The following sections depict the design of the Difficulty level Model and the corresponding of Difficulty level Model with IDR Table. Several testing have been conceded for reliability testing of the IDD Personalizing Model.

3 The Design of Difficulty Level Model

After defining the fuzzy set, a generic graph was plotted against the number of question to be set and the level of difficulty. A difficulty level diagram with 11 difficulty level positioned at x-axis has been proposed in the graph. The number 11 has been chosen instead of other values due to the intention of producing a difficulty level range of 10. There are two saturated levels (0 and n) which is positioned at the y-axis. The saturated levels are used to determine the number of maximum and minimum questions to be set in an assessment. With the assistance of fuzzy logic rules, the moderate difficulty level was then determined. Figure 1 shows the Generic difficulty level diagram.

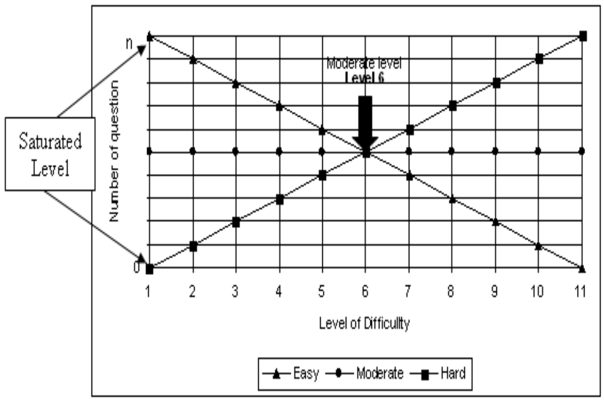

Fig. 1: Generic difficulty level diagram

In order to verify and examine the correctness and effectiveness of the proposed difficulty level model, the number of question at y-axis has been fixed to 10. In other words, the number of questions for both easy and hard levels at the saturated levels is either set to 0 or 10. Figure 2 shows the test-bed graph for the difficulty level model.

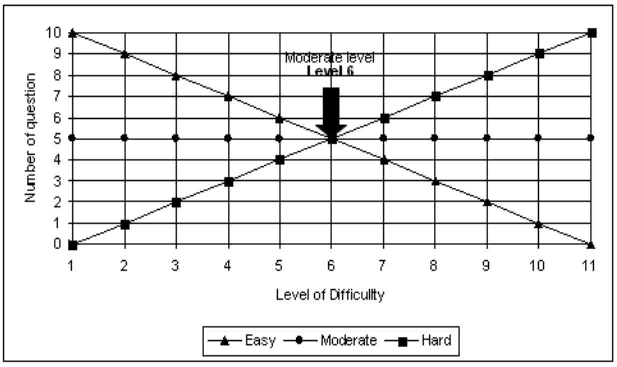

Fig. 2: Test-bed graph

4 The corresponding of Difficulty Level Model with IDR Table in Personalized Learning Assessment Module

Range (%)	Number of level to be increased or decreased	Difficulty Level	Number of		
			Easy Questions	Moderate Questions	Hard Questions
81-100	+5	11	0	5	10
61-80	+4	10	1	5	9
41-60	+3	9	2	5	8
21-40	+2	8	3	5	7
1-20	+1	7	4	5	6
0	0	6	5	5	5
-(1-20)	-1	5	6	5	4
-(21-40)	-2	4	7	5	3
-(41-60)	-3	3	8	5	2
-(61-80)	-4	2	9	5	1
-(81-100)	-5	1	10	5	0

Table 1: Increment & Decrement Reference (IDR) Table

Eight scenarios have been examined by using the Difficulty level model and the IDR Table. Several assumptions have to be made for each scenario based on the preliminary research which has been done in [7].

Assumption I: Let all the passing marks for the assessments set to be 80%.
Scenario 1:
Assuming that a learner has a previous score of 90% and the learner's current level of difficulty is at level 9. From Table 1, the learner will be given 2 easy questions, 5 moderate questions and 8 hard questions in the next assessment.

If in the next assessment, the learner only manages to get 60% of the score, which means that the learner has failed the current assessment. The range between current score with the previous score is (60-90) = -30%. The score difference that the learner had obtained is under negative region of IDR Table, which indicates that there should be a decrement of level if the learner retakes the assessment. From the IDR Table at Table 1, the number of level to be decrease is 2. As a result, the level of difficulty for the retake assessment will be set to (9-2) = 7. From the question pool result at Table 1, the learner will be given 4 easy questions, 5 moderate questions and 6 hard questions in the retake assessment.

From the above scenario, it can be concluded that the personalized learning assessment module is deft to decrease the difficulty level to the correspondent learner when the learner fails an assessment.

Scenario 2:
Assuming that a learner has a previous score of 90% and the learner's current level of difficulty is at level 9 and the learner manages to score 95% after retaking the assessment.

The differences between the learner's current score with the previous score is now (95%-90%) = 5%. (The previous score of the learner is 90%. Once the learner has passed the current assessment, the current score of the assessment will become the previous score for the learner.) The score difference that the learner had obtained is under positive region of IDR Table, this means that the system will automatically increases the level of difficulty by 1. As a result, the next assessment level of difficulty will be set to (9+1) = 10 for that learner. From the test-bed questions result at Table 1, the learner will be given 1 easy question, 5 moderate questions and 9 hard questions in the next assessment.

From the above scenario, it shows that the personalized learning assessment module is able to increase the difficulty level to the correspondent learner when the performance of the learner in the current assessment is improved.

Scenario 3:
Assuming that a learner has a previous score of 90% and the learner's current level of difficulty is at level 11 and the learner manages to score 90% for the current assessment. For this scenario, there will be no increment or decrement of the level of difficulty according to the IDR Table. Therefore, the next assessment level of difficulty for that learner will be remained at level (11+0) = 11.

However, the maximum and minimum levels of difficulty for the Difficulty Level Model are only up to level 11 and level 1 respectively. Assuming that if a learner current level of difficulty is at level 2 and his previous score is 80% and he fails the current assessment with only 20% scores. According to the IDR Table, the range differences that he might obtain is (20-80) = -60%, which means that the difficulty level for the learner to retake the assessment will become (2-3) = -1. However, level 0 or lesser level is a veto for the model. As a result, the difficulty level for the retake assessment will be automatically set to the saturated level which is level 1, the minimum level.

From the above scenario, it can be concluded that the personalized learning assessment module will automatically imply that there will be no decrement or increment of level if the level of difficulty has reached the saturated level.

Assumption II: Let's assume that the passing marks for all the assessments are set to 60%.

Scenario 4:
Assuming that a learner has a previous score of 90% and the learner's current level of difficulty is at level 9. If in the next assessment, the learner only manages to get 60% of the score, which means that the learner just passed the current assessment. The range between current score with the previous score is (60-90) = -30%. From the IDR Table, the number of level to be decrease is 2. As a result, the next assessment level of difficulty will be set to (9-2) = 7 for that learner.

Scenario 5:
Assuming that a learner has a previous score of 60% and the learner's current level of difficulty is at level 6 and the learner manages to score 85% after retaking the assessment. The differences between the learner's current score with the previous score is now (85%-60%) = 25%. The score difference that the learner had obtained is under the positive region of IDR Table, this means that the system will automatically increase the level of difficulty by 2. As a result, the next assessment level of difficulty will be set to (6+2) = 8 for that learner.

From both scenario 4 and 5, it has been proven that the personalized learning assessment module is able to perform well although the passing marks for all the assessments has been down graded.

Assumption III: Let's assume that the passing marks for all the assessments are set to 85%.
Scenario 6:
Assuming that a learner has a previous score of 90% and the learner's current level of difficulty is at level 9. If in the next assessment, the learner only manages to get 60% of the score, which means that the learner has failed the current assessment. The range between current score with the previous score is (90-60) = -30%. The result will be similar as in scenario 1.

Scenario 7:
Assuming that a learner has a previous score of 85% and the learner's current level of difficulty is at level 11 and the learner manages to score 95% in the current assessment. The differences between the learner's current score with the previous score is now (95%-85%) = 10%. According to the IDR Table, the difficulty level for the learner to take the next assessment will still remain level 11 which is the saturated level.

From both scenario 6 and 7, it has been verified that the personalized learning assessment module will not be affected even though the passing marks for all the assessments has been up graded.

Assumption IV: Let's assume that the passing marks for all the assessments are set to 80%.
Scenario 8:
Assuming that a learner does not has any previous result and the learner's current level of difficulty is set to a default level (level 6). If in the current assessment, the learner manages to score 100% which means that the next assessment level of difficulty will be set to (6+1) = 7 for that learner (20% of differences between the passing marks and the current score). If in the next assessment, the learner manages to get 100% of score again, the next assessment level of difficulty for the learner will auto increment by 1 although the differences between the previous score and current score = 0%. The process of auto increment by 1 will be repeating if the learner obtains 100% for his/her current assessment again until a saturated level has been reached.

In scenario 8, it has been proven that the personalized learning assessment module is able to increase the level of difficult until a saturated level although a learner manages to obtain perfect scoring in all the assessments.

5 Conclusion and Future Work

This paper has presented the IDD Personalizing Model which uses the co residential of Increment & Decrement Reference (IDR) Table and Difficulty Level Model which we believe is the strength and winning edge over other e-learning systems. For future work, we will be reviewing and revising the IDD Personalizing Model. Besides, the size of the question pool will be increased from time to time by conducting more surveys and evaluating the survey result. We strongly believe that the IDD Personalizing Model which has been developed will become a value added component for other e-learning systems in future.

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