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Motivation Assessment Model using Fuzzy Logic in Programming Tutoring System

Rajermani Thinakaran[1,2], Rosmah Ali[1], Morina Abdullah[1], Kamilah Radin Salim[1] and Suraya Yaacob[1]

[1]Advanced Informatics School, UTM Razak School, Universiti Teknologi Malaysia International Campus, Jalan Sultan Yahya Petra, 54100, Kuala Lumpur, Malaysia; rajermani@nilai.edu.my, rosmaha.kl@utm.my, morina.kl@utm.my, kamilah.kl@utm.my, suraya.yaacob@utm.my
[2]Department of Computing, Faculty of Science and Technology, Nilai University, Nilai, Negeri Sembilan, Malaysia

Abstract

Motivation is a key success factor in learning programming. However, motivation aspect has not been fully addressed in Programming Tutoring System. This paper proposed a Motivation Assessment Model for Programming Tutoring System. The aim is to detect and measure students' motivation level so that the tutoring system can deliver the tutorial materials accordingly, much like a human tutor does. In this study, various motivation factors, variables and techniques for measuring students' motivation in tutoring system were investigated. Based on self-efficacy theory, Effort, Choice of Activities, Performance and Persistence were proposed as motivation factors. Parameter(s) for each factor and Fuzzy Logic as a prediction technique were also discussed. As for future work, the proposed model will be implemented in Java platform and tested on programming students using Moodle.

Keywords: Fuzzy Logic, Motivation, Motivation Assessment Model, Programming Tutoring System, Self-Efficacy Section

1. Introduction

Programming knowledge and skills are important for Computer Science students. However, students often find programming concepts and skills very challenging to understand and master. This leads to decreased motivation and high drop outs from the course. Some educators have proposed and used technology-enhanced learning systems[1-4] known as Programming Tutoring System (PTS) to motivate students in learning programming.

According to Cohen[2], students can acquire knowledge up to four times more effectively using technology-enhanced methods compared to traditional education approaches. C. Sylvia[3] and Oztekin[4] also agreed that teaching and learning is more effective with technology-based method compared to traditional lecture-based approach.

There are many PTSs developed to support learning programming. Most of the PTSs motivate students by using animation, visualization, games, and simulation approaches[5]. In learning programming, motivation is considered as an important factor[1,6,7]. Thus, the same consideration needs to be taken account in PTSs.

The rest of this paper is organized as follows: Section 2 presents a brief discussion on PTSs, motivation assessment model and classification techniques. Section 3 proposes a motivation assessment model. Finally, Section 4 concludes the paper and provides suggestions for future work.

**Author for correspondence*

2. Related Works

In this section, some earlier works on PTSs, motivation assessment model and classification techniques are discussed in general.

2.1 Programming Tutoring Systems

PTSes have been actively researched for their effectiveness in assisting teaching and learning programming. PTS is derived from Intelligent Tutoring System (ITS). This idea is to imitate a one-to-one human tutoring learning process where students can receive tutelages, solve exercises and get prompt feedbacks. The main intention is to improve students' learning process and enhance their knowledge in programming.

There are many PTSes developed to support the learning process in programming, but they mostly focus on knowledge and skills while others focus on errors and misconceptions[5]. Since motivation is an important factor for learning programming, many PTSes try to engage students by using different approaches such as animation, visualization, games, and simulation.

2.2 Motivation Assessment Model

Motivation and learning are highly complex aspects of human behavior. Motivation has been agreed as an important factor affecting learning behavior, learning process and learning achievement[8,9]. Hallam[10] stressed the importance of motivation: "if you lose your motivation, you lose just about everything". In learning programming, the same belief holds: commitment in continued practice would not happen without high motivation.

Students obtain their knowledge from previous experiences, while their enthusiasm to learn is affected by a set of motivating factors. The motivating factors can be divided into two types which are intrinsic and extrinsic. Intrinsic factors come from the students' inner self such as student's values, desires, interests and attitudes during learning[11]. Meanwhile, extrinsic factors may come from external conditions such as remuneration, appreciation, punishment, social pressure and competition[11]. de Vicente[12] suggested that motivational factors can be divided into trait (permanent) and state (transient) characteristics of the student. Trait factors consist of control, challenge, independence and fantasy. State factors consist of confidence, sensory interest, cognitive interest, effort and satisfaction.

In a tutoring system, various motivation assessment models have been proposed by researchers using different motivation theories, taxonomies and models[1]. Different motivation factors are considered to evaluate student motivation states (Table 1). These motivational factors are all potential factors that may affect student learning.

Self-efficacy beliefs have a stronger correlation compared to other motivation factors[13]. For learning, self-efficacy is an important factor that drives students' performance. Self-efficacy refers to what a student believes he/she can do in a particular learning task. Self-efficacy concept was introduced by Albert Bandura, a Canadian psychologist[14]. He defined self-efficacy as "… people's judgments of their capabilities to organize and execute courses of action required to attain designated types of performances". Bandura also claimed that self-efficacy beliefs affect: i) choice of activities a student takes part in; ii) the level of student effort expended in performing a task; iii) persistence in the face of difficulties in completing a task, and iv) student performance in the task[15,16].

Table 1. Different motivation factors[1]

Motivation Factors				
Attention	Effort	Effect	Interest	Self-Esteem,
Clear Direction	Energization	Goal Orientation	Importance	Self-Regulation
Confidence	Engagement	Independency	Reward And Recognition	Self-Efficacy
Confusion	Expectation	Individual Attitude	Source	Task Value

Askar and Umay[17] stated that students with a high perception of self-efficacy in a particular situation would strive to accomplish a task. Hence, self-efficacy is an important phenomenon that needs to be focused on. For instance, a student might approach a programming question with the view that: "I tend to find programming difficult (a self-efficacy belief) so I am likely to need a lot of help to complete the task (outcome expectation)". These beliefs are likely to become a frame of reference that influences students' thoughts, emotions and engagement in a learning situation.

2.3 Motivation Factor

As claimed by Bandura, Effort, Persistence, Choice of Activities and Performance are the factors affecting student self-efficacy[15,16]. Kim et al[18]. defined Effort as the amount that the student is employing himself/herself in order to perform the learning activities, while del Solato and Du Boulay described Persistence as constancy in performing an activity[19]. Choice of Activities is defined as the level of challenging task the student chooses[18,20]. The task can be of basic, intermediate or advanced level[21,22]. Performance explains the student's achievement on a specific topic. The achievement can be poor, good or excellent.

Table 2 presents the measures of each of the stated motivation factors, with different variables, which have been suggested by different researchers. Most of the researchers considered the number of help/hint requests and time spent to perform a task as parameters to measure effort[6,12,18,19,22,23]. Difficulty level of tasks such as low, medium, high, has been considered as a variable to measure choice of activities[18,20,24]. For performance, Bica at el[21]., Cocea and Weibelzahl[22] suggested the number of correct answers as a variable to measure performance. Number of questions skipped or not answered is used to measure persistence[25].

Table 2. Motivation factors and variables

Researcher(s)	Variable(s)	Descriptions
Motivation Factor : *Effort*		
Ramaha et. al[6]	time and help	time spent on the task, number of help requests
de Vicente and Pain[12]	giving up	number of students giving up and student performance
del Solato and Du Boulay[19]	help or hint	number of help or hints requests to perform a task
Kim et al[18].	help	number of help requests
Cocea and Weibelzahl[22]	help and average time help	number of times help requested and average time help requested
Qu and Johnson[23]	time	estimating how much time the student spent on task.
Motivation Factor : *Choice of Activities*		
Kim at el[18].	level of problems	level of solving problems (high, medium, low)
Juarez-Ramirez[20]	complexity level	complexity level of task (basic, intermediate, advanced)
McQuiggan and Lester[24]	type of questions and difficulty level	contains three types of questions: fill in, single choice and multiple choice with difficulty level (very easy, easy, medium, hard, very hard)
Motivation Factor : *Performance*		
Bica at el[21].	number of correct answers	number of correct answers in the tutorial
Cocea and Weibelzahl[22].	number of correct and incorrect answers	number of correct answers, number of incorrect answers and their averages
Motivation Factor : *Persistence*		
Narciss et al[25].	skipping questions	skipping questions (either intentionally, or unintentionally, without even request help or hint)

2.4 Prediction Technique

To predict student motivation level and find remedial actions, a prediction technique needs to be considered. There are different types of prediction techniques available such as Item Response Theory[25], Dynamic Mixture Model (combining a hidden Markov model with Item Response Theory)[26], Bayesian Network[27], Latent Response Model[28] and Fuzzy Logic[29].

Cristobal et al[30]. in their research, have tested different kind of classification techniques, and recommended Fuzzy Rule Learning or Fuzzy Logic technique. This classification technique provides comprehensible results, allows an interpretation of the model obtained and can be used for making decisions. Fuzzy classification technique has been built in the web-based learning system to present student's knowledge level[32]. The learning system shows an improvement on personalization of learning and promotes effective learning.

Chrysafiadi and Virvou[30] suggested that fuzzy logic techniques can be used to improve the performance of an eLearning environment. According to Shakouri and Menhaj[33], fuzzy logic algorithm based on fuzzy decision making helps to select the optimum model by considering a set of criteria and model specifications. Indeed as proposed by Chrysafiadi and Virvou[30], the integration of fuzzy logic into a tutoring system can increase students' satisfaction and performance, improve the system adaptivity and help the system to make more valid and reliable decisions.

2.5 Fuzzy Logic

Fuzzy theory was proposed by Dr. Lotfi Zadeh, The aim is to capture the vagueness to describe concepts, objects, events, phenomena or statements. Fuzzy Logic consists of three steps: (1) Fuzzification; (2) Rule Evaluation and (3) Defuzzification known as Fuzzy Inference System. It is the process of formulating the mapping from a given input to an output using membership functions, fuzzy logic operators and IF-THEN rules. The mapping then provides a basis from which decisions can be made.

Membership function is a curve that defines how each point in the input space is mapped to a membership value between 0 and 1, and is also a fundamental block of fuzzy set theory. There are eleven built-in membership function types. The simplest and most common types used are trapezoidal and triangular[35].

3. Proposed Fuzzy Logic Motivation Assessment Model

Most of the PTSes are concerned with design aspects of the instructional process, overlooking the motivational aspects. In this study, the authors proposed a motivation assessment model based on self-efficacy theory and Fuzzy Logic as the classification technique to assess student motivation level in the PTS.

Since PTS is derived from ITS, the proposed PTS uses ITS architecture composed of four models[36]. The models are: i) Domain Model - contains processes, theories, and problem-solving schemes of the domain to be learned, ii) Student Model - gives special alertness to student's cognitive and affective states and his/her progress in the learning process, iii) Tutor Model - accepts information from the domain model and uses the student model for making decisions on tutoring plans and actions, iv) Student Interface Model - provides the interface with which the student interacts with the system.

In addition to this architecture, a Motivation Assessment Model will be integrated to evaluate the student motivation level. The model will select appropriate tutorial materials for the student based on the identified motivation level.

The proposed Motivation Assessment Model is based on self-efficacy theory. The model consists of four motivation factors which are Effort, Choice of Activities, Performance and Persistence. These motivation factors are used to determine students' motivation level and provide tutorial module accordingly.

Fuzzy logic will be used as the prediction technique for the proposed assessment model. In this study, triangular MF has been chosen based on minimum error in prediction of data[34], and for being simple to implement and fast in computation[37].

The inference rules are based on self-efficacy motivation factors, which are *effort* $\rightarrow EF(x)$, *choice of activity* $\rightarrow CA(x)$, *persistence* $\rightarrow PS(x)$, *performance* $\rightarrow PF(x)$.

For *effort*, the time spent to solve the questions will be the parameter and the rule is denoted as

$$EF(x) = \{Short, Medium, Long\} \tag{1}$$

There are there fuzzy sets (Figure 1) defined for the 'time spent': *Short* refers to how fast a task had been resolved, *Medium* for average task resolving and *Long* for very slow task resolving. The value of the parameter depends on the average time that the instructor sets for solving a particular set of questions.

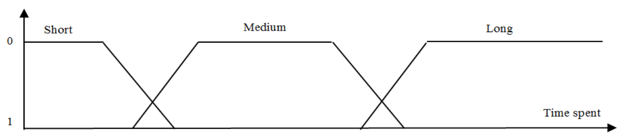

Figure 1. Fuzzy parameter: Effort.

For *choice of activities*, the level of challenging question will be the parameter and the rule is denoted as

$$CA(x) = \{Easy, Medium, Hard\} \tag{2}$$

The 'challenging question' parameter depends on the difficulty of each particular question. It is calculated as the average value of difficulty of all questions that a student has to resolve. 'Challenging question' has three fuzzy sets (Figure 2): *Easy* as 1, *Medium* as 2 and *Hard* as 3 which describes the difficulty level of the questions.

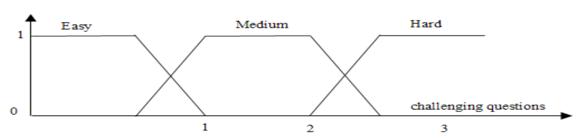

Figure 2. Fuzzy parameter: Choice of Activities.

The number of correct answers will be the parameter for *performance* and the rule is denoted as

$$PF(x) = \{Poor, Good, Excellent\} \tag{3}$$

There are there fuzzy sets (Figure 3) defined for the 'number of correct answers' on the question: *Poor*, *Good* and *Excellent*. It is calculated as the total number of questions minus with total number of question(s) answered wrongly by the student in the range from 1 to 100 in percentages.

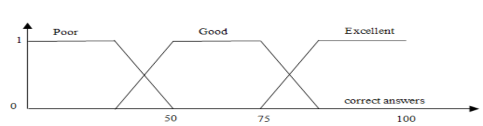

Figure 3. Fuzzy parameter: Performance.

For persistence, the number of skipped questions will be the parameter and the rule is denoted as

$$PS(x) = \{Low, Medium, High\} \tag{4}$$

The 'number of skipped questions' parameter depends on how many questions a student does not answer. It is calculated as the total number of questions minus the total number of question(s) answered by the student in the range from 1 to 100 in percentages. The 'Number of skipped questions' has three fuzzy sets (Figure 3) which are *Low, Medium* and *High*.

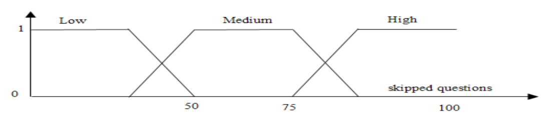

Figure 4. Fuzzy parameter: Persistence.

All possible combinations of inference rules are represented in eighty-one rules in the form of IF-THEN statements. The output of motivation level can be denoted as *ML(x) = {Low, Medium, High}*. Figure 5 shows one of rules used to identify student motivation level. This output can be used to deliver appropriate tutorial materials in PTS to aid in student learning process. Overall, Figure 6 shows the Fuzzy Inference System for the proposed Motivation Assessment Model.

IF (EF == '*Short*') AND (CA == '*Easy*') AND (PF == '*Poor*') AND (PS == '*Low*')
THEN
(ML == '*Low*')

Figure 5. Example of a rule-based decision.

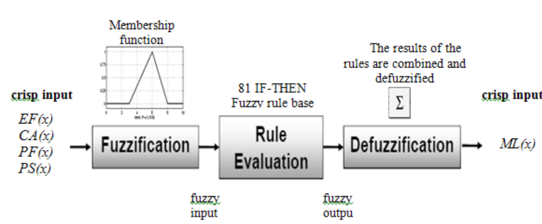

Figure 6. Fuzzy Inference System for Proposed Fuzzy Logic Motivation Assessment Model.

4. Conclusion and Future Work

Prediction of student motivation level holds great promise for PTSs. The proposed model can be used to detect student motivation level during the learning process in PTS. Detection of student motivation level can assist the tutoring system in providing appropriate tutorial materials, much like a human tutor does. This model describes all the steps of making inferences starting from fuzzification, rule evaluation and defuzzifiction. The tutoring system can provide recommendations in an automatic manner based on a student's motivation level, much like in the traditional classroom. As for future work, the proposed model will be implemented in Java platform and tested on programming students using Moodle.

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