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B^2 model: A browsing behavior model based on High-Level Petri Nets to generate behavioral patterns for e-learning

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ABSTRACT

As Internet use has proliferated, e-learning systems have become increasingly popular. Many researchers have taken a great deal of effort to promote high quality e-learning environments, such as adaptive learning environments, personalized/adaptive guidance mechanisms, and so on. These researches need to collect large amounts of behavioral patterns for the verification and/or experimentation. However, collecting sufficient behavioral patterns usually takes a great deal of time and effort. To solve this problem, this paper proposes a browsing behavior model (B^2 model) based on High-Level Petri Nets (HLPNs) to model and generate students' behavioral patterns. The adopted HLPN contains (1) Colored Petri Nets (CPNs), in which colored tokens can be used to identify and separate student, learning content and assessment, and (2) Timed Petri Nets (TPNs), in which time variable can be used to represent the time at which a student reads learning content. Besides, to validate the viability of the B^2 model, this paper implements a B^2 modeling tool to generate behavioral patterns. The generated behavioral patterns are compared with actual behavioral patterns collected from elementary school students. The results confirm that the generated behavioral patterns are analogous to actual behavioral patterns.

1. Introduction

With the rapid advance of the Internet, e-learning systems have become more and more popular (Gomez-Albarran, 2005; Su, Tseng, Chen, Weng, & Tsai, 2006). An e-learning system provides the following functions: (1) delivery of learning content for students via the Internet; (2) record of learning progress and portfolio; (3) management of learning content, assessment and course; and so on (SCORM, 2004). The learning content is composed of one or more learning resources, such as a HTML file and a Flash file (SCORM, 2004). One of the important advantages of e-learning is the adaptive learning environments, in which the providing of learning content must meet individual student's demand (Brusilovsky, 1999; Brusilovsky, Eklund, & Schwarz, 1998; Brusilovsky & Maybury, 2002). Adaptive learning environments have been proved that it facilitates student to learn more efficiently and effectively (Carver, Howard, & Lane, 1999; Papanikolaou, Grigoriadou, Magoulas, & Kornilakis, 2002). To realize adaptive learning environments, numerous researches have been devoted in providing appropriate learning content for individual students (Canales, Pena, Peredo, Sossa, & Gutierrez, 2007; Chu & Chang, 2007). For instance, Tang and Mccalla (2003) proposed an evolving web-based learning system, which finds a relevant learning content according to the accumulated ratings given by students (Tang & Mccalla, 2003). Liu and Yang (2005) proposed the Adaptive and Personalized E-Learning System (APeLS), which provides dynamic learning content and adaptive learning processes for students to enhance the quality of learning (Liu & Yang, 2005). In addition, many personalized/adaptive guidance mechanisms have been proposed to provide the personalized/adaptive learning paths for different students (Chen, Lee, & Chen, 2005; Weber & Specht, 1997), such as, Papanikolaou et al. (2002) integrated theories of instructional design with learning styles to develop a framework that adapts different students to provide the presentation sequence of the learning content in a lesson (Papanikolaou et al., 2002). Chen (2008) proposed genetic-based personalized e-learning system to (i) generate appropriate learning paths according to the incorrect testing responses of an individual student in a pre-test, and (ii) provide benefits in terms of learning performance promotion (Chen, 2008).

Behavioral patterns refer to the learning records in an e-learning system, which contain (i) the time at which a student reads learning content or undertakes assessments, (ii) the score that a student receives from an assessment, and so on. Since the aforementioned personalized/adaptive learning methods validate their availability by experimentation, they need to collect behavioral patterns. For example: in Papanikolaou et al.'s research, the reactions of 10 undergraduate students are acquired for corroborating the assumption that different instructional strategies should be applied to different students (Papanikolaou et al., 2002). In Liu and Yang's research, the

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achievement of 120 students are collected and used to evaluate whether the learning path provided by the APeLS can obtain better learning quality for the students (Liu & Yang, 2005). Chu and Chang collected the learning behavioral features of 117 elementary school students to corroborate the accuracy of the prediction mechanism (Chu & Chang, 2007). Chen et al. collected the satisfaction evaluation of 210 students for determining whether or not the recommended learning content meets most students' requirements (Chen, Lee, et al., 2005). To evaluate whether or not the learning mode of curriculum sequencing recommendation is superior to the freely browsing learning mode, Chen invited 220 third grade elementary school students to participate in the experimentation (Chen, 2008).

However, building an e-learning system for collecting behavioral patterns requires a great deal of time and effort. Besides, collecting sufficient behavioral patterns is often time consuming, such as collecting the learning behavioral features of 117 elementary school students takes one month (Chu & Chang, 2007), and collecting the results of assessments takes over 2 years (Carver et al., 1999). To obtain behavioral patterns easily, this paper proposes a browsing behavior model (B^2 model) based on High-Level Petri Nets (HLPNs) to model and generate behavioral patterns. HLPN is extended from Petri nets (PNs) (Murata, 1989; Peterson, 1977; Peterson, 1981) using color token to model data (Jensen, 1992), time variable to simulate time (Ramchandani, 1974; Wang, 1998), hierarchy to structure large models (Fehling, 1993), and fuzzy rule-based reasoning for the framework of propositional logic (Koriem, 2000; Looney, 1988). We observe that (i) the colored tokens of Colored Petri Nets (CPNs) (Jensen, 1992) can be used for identifying and separating student, learning content and assessment, and (ii) the time variable of Timed Petri Nets (TPNs) (Ramchandani, 1974; Wang, 1998) can be used to represent the time at which a student reads learning content. Thus, this paper uses both the CPN color set and the TPN time parameters to accurately model behavioral patterns in e-learning environments, namely B^2 model.

To validate the viability of the B^2 model, this paper compares actual behavioral patterns collected from elementary school students with the generated behavioral patterns based on the B^2 model, and then analyzes the availability of the B^2 model. The compared results corroborate that: The generated behavioral patterns are analogous to actual behavioral patterns collected from elementary school students, which exhibits the accuracy of the B^2 model. Besides, since the generated behavioral patterns are analogous to the actual behavioral patterns, the B^2 model is capable of predicting the appropriate learning content for individual students to achieve adaptive learning environments.

The rest of this paper is organized as follows: Section 2 briefly reviews the basic concepts of PN and the applications of HLPN. Section 3 presents the B^2 model in detail. Section 4 takes an example to explain the execution of the B^2 model. Section 5 demonstrates the implementation of the B^2 model and evaluates the generated behavioral patterns. Finally, Section 6 concludes the paper.

2. Related works

Both CPN and TPN are derived from Petri Nets (PNs), called High-Level Petri Nets (HLPNs). This section briefly reviews the basic concepts of PN in sub-Section 2.1 and the related applications of HLPN in sub-Section 2.2.

2.1. The basic concepts of PN

PN is a graphical and mathematical modeling tool which possesses the advantages of graphical notation and simple semantics (Dwyer & Clarke, 1996; Koriem, 2000; Murata, 1989). Fig. 1 shows an example of PN.

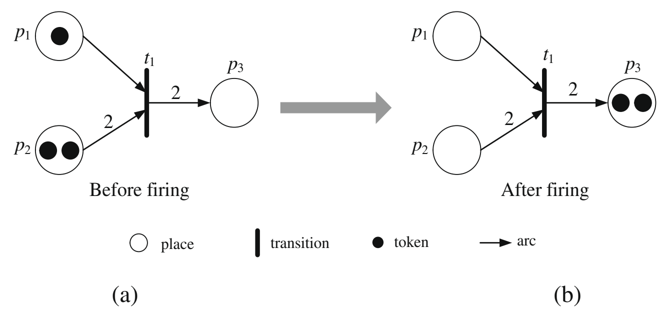

Fig. 1. An example of Petri Nets.

A PN is a 5-tuple (Murata, 1989; Peterson, 1977; Peterson, 1981):

$$PN = (P, T, A, W, M_0), \tag{1}$$

where

(1) $P = \{p_1, p_2, \ldots, p_m\}$ is a finite set of places. A place represents a circle, such as, p_1, p_2 and p_3 in Fig. 1.
(2) $T = \{t_1, t_2, \ldots, t_n\}$ is a finite set of transitions. A transition represents a bar, such as t_1 in Fig. 1. The intersection of P and T is an empty set, while the union of P and T is not an empty set, i.e., $P \cap T = \emptyset$ and $T \cup P \neq \emptyset$.
(3) $A \subseteq (PxT) \cup (TxP)$ is a set of arcs connecting places and transitions, such as the arrowhead from p_1 to t_1 depicted in Fig. 1.
(4) $W : A \rightarrow \{1, 2, 3, \ldots\}$ is a weight function, whose weight value is positive integers. Arcs, i.e., arrowhead, are labeled with weights. For example, in Fig. 1, the arrowhead from t_1 to p_3, which is labeled with "2", is denoted as $W(t_1, p_3) = 2$. When the weight is unity and/or "1", the label of arc is usually omitted, e.g., $W(p_1, t_1) = 1$ is omitted in Fig. 1.
(5) $M_0 : P \rightarrow \{0, 1, 2, 3, \ldots\}$ is the initial marking. If there are k tokens inside place p_i, it is said that p_i is marked with k tokens. For example, in Fig. 1a, p_1 is marked with one token, which is denoted as $M(p_1) = 1.p_2$ is marked with two tokens, which is denoted as $M(p_2) = 2$. If Fig. 1a is the initial status, the initial marking is denoted as $M_0(p_1, p_2, p_3) = \{1, 2, 0\}$.

A transition t is said to be fired if all its input places p_i are marked with at least $W(p_i, t)$ tokens, where $W(p_i, t)$ is called the firing condition of transition t. For example, in Fig. 1, the firing conditions of t_1 are $W(p_1, t_1) = 1$ and $W(p_2, t_1) = 2$.

A firing transition t removes $W(p_i, t)$ tokens from each input place p_i, and adds $W(t, p_j)$ tokens to each output place p_j. For instance, since $M(p_1) = 1$ and $M(p_2) = 2$ have satisfied the firing conditions of t_1 in Fig. 1a, t_1 is fired. After t_1 is fired as Fig. 1b depicts, t_1 has removed $W(p_1, t_1) = 1$ token from input place p_1 of t_1 and $W(p_2, t_1) = 2$ tokens from input place p_2 of t_1, respectively, and then added $W(t_1, p_3) = 2$ tokens to output place p_3 of t_1.

2.2. The related applications of HLPN

PN lacks the concepts of data and hierarchy. Consequently, the models based on PN often become excessively large and complex. Hence, many kinds of High-Level Petri Nets (HLPNs), e.g., Colored Petri Nets (CPNs) (Jensen, 1992), Timed Petri Nets (TPNs) (Ramchandani, 1974; Wang, 1998) and Fuzzy Petri Nets (FPNs) (Koriem, 2000; Looney, 1988), have been proposed to overcome the weaknesses of PN.

Current existing applications of HLPN in terms of e-learning field are as follows: (1) In 2002, to reuse and aggregate learning