Expert Systems with Applications 41 (2014) 1369–1376

Contents lists available at ScienceDirect

Expert Systems with Applications

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

Dynamic representation of fuzzy knowledge based on fuzzy petri net and genetic-particle swarm optimization

Wei-Ming Wang *, Xun Peng, Guo-niu Zhu, Jie Hu, Ying-Hong Peng

School of Mechanical Engineering, Shanghai Jiao Tong University, Shanghai 200240, China

ARTICLE INFO

Keywords:
Fuzzy knowledge
Petri nets
Knowledge representation
Learning algorithms
Particle swarm optimization

ABSTRACT

Information in some fields like complex product design is usually imprecise, vague and fuzzy. Therefore, it would be very useful to design knowledge representation model capable to be adjusted according to information dynamics. Aiming at this objective, a knowledge representation scheme is proposed, which is called DRFK (Dynamic Representation of Fuzzy Knowledge). This model has both the features of a fuzzy Petri net and the learning ability of evolutionary algorithms. An efficient Genetic Particle Swarm Optimization (GPSO) learning algorithm is developed to solving fuzzy knowledge representation parameters. Being trained, a DRFK model can be used for dynamic knowledge representation and inference. Finally, an example is included as an illustration.

1. Introduction

In the real world, there exist many problems people have not had a fundamental understanding of, and the information people are obtaining is uncertain information. Most human knowledge, how-ever, is typically expressed in vague and imprecisely defined concepts and the inference is mostly supported by common-sense and intuitive reasoning (Ribaric & Hrkac, 2012).

Aiming to problem solving in specific areas, the knowledge-based systems depends not only on theoretical knowledge determined in specific areas, but more on experience and common sense of experts. The uncertainty of objective things or phenomena in the real world leads to the fact that people's information and knowledge in various cognitive domains are mostly inaccurate, which requires that the knowledge representation and processing model in the expert system can reflect this uncertainty. Therefore, how to represent and process the uncertainty of knowledge has become one of the important research issues on artificial intelligence.

There are important issues underlying knowledge representation that have not yet been adequately addressed. Such issues are those of the modeling and verification of the knowledge-based systems (Ashon, 1995; Mengshoel & Delab, 1993). As a case in point, the conventional techniques such as simulation methods and analytical methods do not provide tools for representing the dynamic behavior of the KBSs as well as for modeling the different aspects of fuzzy information of these systems (Garg, Ahson, & Gupta, 1991; Polat & Guvenir, 1993; Zadeh, 1989).

As an important modeling and computational paradigm, Petri nets (PN) have been widely used (Murata, 1998). Machine learning with fuzzy AND-OR neurons and with fuzzy Petri nets have been proposed by Pedrycz (1989). In order to deal with uncertain information or knowledge, fuzzy Petri nets (FPNs) have been introduced, which can be used to represent Horn clauses or Non-Horn clauses and represent and execute the fuzzy rules (Jeffrey, Lobo, & Murata, 1996; Konar & Mandal, 1996). To improve the FPN adjusting (or learning) ability, a generalized fuzzy Petri net (GFPN) is proposed (Pedrycz & Gomide, 1994). To solve the learning problem, an adaptive fuzzy Petri net (AFPN) is proposed by adjusting weights the same as those in a neural network (NN) (Looney, 1994). But the weight adjustment is off-line. To overcome this weakness, several researchers have recently investigated FPN learning ability by using evolutionary algorithms (Huang, Yang, Wang, & Tsai, 2010). In fact, the knowledge learning above was under the framework of neural networks. Adaptive Fuzzy Petri Net (AFPN) has also the learning ability of a neural network, but it does not need to be transformed into neural networks, and Back Propagation algorithm is developed for the knowledge learning under generalized conditions (Li & Lara-Rosano, 2000). However, the learning algorithm is based on a special transition firing rule, it is necessary to know certainty factors of each consequence proposition in the system. Obviously, this restriction is too strict for a knowledge based system.

Instead of using the Neural Network, this study tries swarm intelligence: particle swarm optimization (PSO). Proposed by Kennedy and Eberhart and inspired by social behavior in nature, PSO is a population-based search algorithm that is initialized with a population of random solutions, called particles (Kennedy, 1995; Kennedy, Eberhart, & Shi, 2001). Each particle in the PSO flies

* Corresponding author. Tel.: +86 (0) 21 34206170; fax: +86 (0) 21 34206179.
E-mail addresses: wangweiming@sjtu.edu.cn, wwm78@sina.com (W.-M. Wang).

0957-4174/$ - see front matter © 2013 Published by Elsevier Ltd.
http://dx.doi.org/10.1016/j.eswa.2013.08.034

through the search space at a velocity that is dynamically adjusted according to its own and its companion's historical behavior. Because particle swarm optimization is powerful, easy to implement, and computationally efficient, numerous researches on PSO theories or applications have been reported Recently (Chatterjee & Siarry, 2006; Jiang & Etorre, 2005; Mendes, Kennedy, & Neves, 2004; Shi, Liang, Lee, Lu, & Wang, 2005).

The rest of the paper is organized as follows. The related work concerning the proposed scheme is introduced in Section 2. The proposed model of dynamic representation of fuzzy knowledge (DRFK) is covered in Section 3. The GPSO learning algorithm for solving knowledge representation parameters is presented in Section 4. An illustrative case study, fault diagnose of launch vehicle is presented in Section 5. Finally, conclusions are drawn in Section 6.

2. Fuzzy production rules and fuzzy Petri net

2.1. Fuzzy production rules

Fuzzy production rules (FPRs) are widely used in knowledge based systems to represent fuzzy and uncertain concepts. FPRs are usually presented in the form of a fuzzy IF-THEN rule in which both the antecedent and the consequent are fuzzy concepts, denoted by fuzzy sets. To effectively represent both the fuzziness and the uncertainty in FPRs, several knowledge parameters such as confidence value, weight, and threshold have been incorporated into FPRs. Thus, a FPR has the following format:

Definition 1. $R: If\ AthenC(CF = \mu), Th, W$

where $A = (a_1, a_2, \ldots, a_n)$ is the antecedent portion which comprises one or more propositions connected by either "AND" or "OR". Each proposition $a_i (1 \leqslant i \leqslant n)$ may have a fuzzy variable of the antecedent. The parameter μ is the confidence value of the rule and it represents the strength of belief of the rule. The symbol *Th* represents a set of threshold values specified for the propositions in the antecedent A. The set of weights assigned to the propositions $a_1, a_2, \ldots, a_n$, is given by $W = (w_1, w_{2,}, \ldots, w_n)$.

2.2. Fuzzy Petri net

Definition 2. *An FPN is a 9-tuple, given by FPN =* $\langle P, Tr, T, D, I, O, Th, n, W\rangle$

where $P = (p_1, p_2, \ldots, p_n)$ is a finite set of places; $Tr = (tr_1, tr_2, \ldots, tr_m)$ is a finite set of transitions; $T = (t_1, t_2, \ldots, t_m)$ is a set of fuzzy truth tokens in the interval [0, 1] associated with the transitions $(tr_1, tr_2, \ldots, tr_m)$,respectively; $D = (d_1, d_{2,\ldots,}d_n)$ is a finite set of propositions, where proposition d_k corresponds to place p_k; $P \cap {}^{T}r \cap {}^{D} = \varnothing$; cardinality of (P) = cardinality of (D); $I{:}Tr \to P^{\infty}$ is the input function, representing a mapping from transitions to bags of (their input) places; $O{:}Tr \to P^{\infty}$ is the output function, representing a mapping from transitions to bags of (their output) places; $TH = (th_1, th_2, \ldots, th_m)$ represents a set of threshold values in the interval $[0, 1]$ associated with transitions $(tr_1, tr_2, \ldots, tr_m)$, respectively; $n{:}P \to [0, 1]$ is an association function hereafter called fuzzy belief, representing a mapping from places to real values between 0 and 1; $n(p_i) = n_i(say)$; $W = w_{ij}$ is the set of weights from the *j*th transition to the *i*th place, where *i* and *j* are integers.

3. The model of dynamic representation of fuzzy knowledge

Fuzzy production rule is one of the most basic researched areas of knowledge based engineering (KBE). We have chosen the fuzzy Petri net (FPN) as an alternative modeling and analysis formalism. FPN formalism is a derivative of PNs which have been demonstrated to be powerful modeling formalisms. Modeling using FPN has many advantages compared to other modeling schemes. The graphic representation of FPN makes the models relatively simple and legible.

The knowledge representation based on FPN has two basic general formulation, shown as "AND" rule representation model based on FPN (as Fig. 1) and "OR" rule representation model based on FPN (as Fig. 2).

The fuzzy production rules based on the Petri Net is shown in Fig. 3, where p_j $(j = 1, 2, \ldots, n)$ denotes the antecedent (premise) part of a given rule, it defines the fuzzy region in the input space; d_i $(i = 1–3)$ denotes the consequent (decision, conclusion) part of that rule, it specifies the output in the fuzzy region; μ_i $(i = 1–3)$ is the confidence value that is associated with the conclusion being pursued. w_{ij} is the weight that weighs the importance of every antecedent to its consequent propositions. λ is the threshold value. The model includes three rules:

IF p_1 and p_2 THEN $d_1(\lambda_1, \mu_1, \omega_{11}, \omega_{12})$

IF p_1 and p_3 and p_4THEN $d_2(\lambda_2, \mu_2, \omega_{21}, \omega_{22})$

IF p_1 and p_4 and p_5THEN $d_3(\lambda_3, \mu_3, \omega_{31}, \omega_{32}, \omega_{33})$

The knowledge representation parameters of the FPN is updated or modified frequently, it may be regarded as dynamic systems. Suitable models for them should be adaptable. In other words, the models must have ability to adjust themselves according to the systems' changes. However, the lack of adjustment (learning) mechanism in FPNs cannot cope with potential changes of actual systems. Therefore, it would be very useful to develop the parameters self-learning mechanism in the FPN capable to be adjusted like human cognition and thinking, according to knowledge dynamics to achieve the dynamic representation of fuzzy knowledge.

The model of DRFK is shown in Fig. 4. Aiming at the adjustment (self-leaning) of the representation parameters in the DRFK, firstly, building the physical model of DRFK based on fuzzy Petri net to organize the fuzzy knowledge representation parameters.

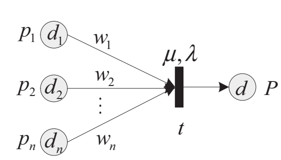

Fig. 1. "AND" rule.

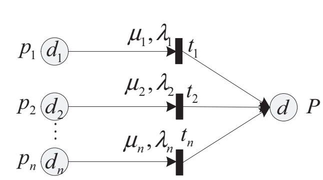

Fig. 2. "OR" rule.

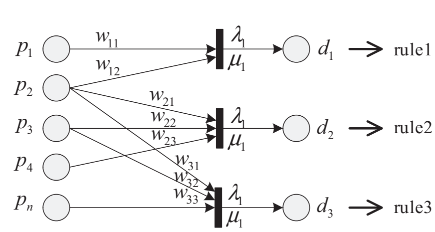

Fig. 3. Fuzzy knowledge representation based on Petri net.