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Medical Diagnostic System Using Fuzzy Coloured Petri Nets under Uncertainty

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Abstract

We propose a medical diagnostic system using Fuzzy Coloured Petri Nets (FCPN) in this paper. For complex real-world knowledge Fuzzy Petri Net (FPN) models have been proposed to perform fuzzy reasoning automatically. However, in the Petri Net we have to represent all kinds of processes by separate subnets even though the process has the same behavior of other one. Real-world knowledge often contains many parts which are similar, but not identical. This means that the total PTN becomes very large. The kind of problems may be annoying for a small system, and it may be catastrophic for the description of large-scale system.

To avoid this kind of problems we propose a learning and reasoning method using FCPNs under uncertainty. On the other hand to correct the rules of knowledge-based system hand-built classifier and empirical learning method both based on domain theory have been proposed as machine learning methods, where there is a significant gap between the knowledge-intensive approach in the former and the virtually knowledge-free approach in the later.

To resolve such problems simultaneously we propose a hybrid learning method which is built on the top of knowledge-based FCPN and Genetic Algorithms (GA).

To verify the validity and the effectiveness of the proposed system, we have successfully applied it to the diagnosis of intervertebral diseases.

Keywords

Fuzzy Coloured Petri Net; Genetic Algorithm; Medical Diagnostic System

Introduction

For many years, one of the research topics of artificial intelligence (AI) has been the development of sufficiently precise notations for knowledge representation. In order to make real-world knowledge suitable for processing by computers, Fuzzy Petri Nets (FPNs) have been proposed. However, in FPNs we have to represent all kinds of processes by separate subnets even though the process has the same behavior of other one.

On the other hand to correct the rules of knowledge-based system hand-built classifiers and empirical learning methods both based on the domain theory have been proposed as machine learning methods.

However, there is a significant gap between the knowledge-intensive, learning-by-being-told approach of hand-built classifiers and the virtually knowledge-free approach of empirical learning.

Some of this gap is filled by the hybrid learning methods, which are both hand constructed rules and classified examples during learning.

Hybrid learning methods use theoretical knowledge of a domain and a set of classified examples to develop a method for accurately classifying examples not seen during training.

To avoid such kind of problems we propose a learning and reasoning knowledge-based FCPNs which is a hybrid learning system built on top of FCPNs and GAs.

To verify the validity and the effectiveness of the proposed method, the system is applied to the diagnosis of intervertebral diseases.

Fuzzy Petri Nets

We can use a Fuzzy Petri Nets [1] to represent the fuzzy production rules of rule-based system. A Fuzzy Petri Nets is bipartite directed graph which contains two types of nodes: places and transitions, where circles represent places, and bar representation. Each place may or may not contain a token associated with a truth value between zero and one. Each transition is associated with a certainty factor value between zero and one. Directed arcs represent the relationships from places to transitions and form transitions to places. The concept of Fuzzy Petri Nets is derived from Petri Nets.

Formal Definition of Fuzzy Petri Net

A generalized FPNs structure can be defined as an 8-tuple:

$$FPN=(P, T, D, I, O, f, ,)$$

where

P is a finite set of places,
T is a finite set of transitions,

D is a finite set of propositions,

$PTD = \varnothing, |P| = |D|$

I is the input function, a mapping from transitions to bags of places,

O is the output function, a mapping from transitions bags of places,

f is an association function, a mapping from transitions to real values between zero and one,

β is an association function, a mapping from places to real values between zero and one,

is an association function, a objective mapping from places to proposition.

Let A be a set of directed arcs. If $P \in I(t_i)$, then there exists a directed arc a_{ji}, $a_{ji} \in A$, from the place p_j to the transition t_i. If $P_k \in (t_i)$, then there exists a directed arc a_{ik}, $a_{ik} \in A$, from the transition t_i to the place p_k. If $f(t_i) = \mu_i$, $\mu_i \in \lceil 0, 1 \rceil$, then the transition t_i is said to be associated with a real value μ_i. If $\beta(p_i) = d, d_i \in D$ then the place p_i is said to be associated with the proposition d_i.

Fuzzy Petri Nets Modeling

A FPNs with some places containing tokens is called a marked Fuzzy Petri Nets (MFPN). In a MFPN, the token in a place p_i is

represented by a labeled dot " • ".

The token value in a place p_i, $P_i \in P$, is denoted by $\alpha(P_i)$, where $\alpha(P_i) \in [0, 1]$. If $\alpha(p_i) \in y_i, y_i \in [0, 1]$, and $\beta(p_i) = d_i$, then it indicates that the degree of truth of proposition d_i is y_i.

By using a FPNs, the fuzzy production rule

R_i: IF d_j THEN d_k (CF=μ_i)

can be modeled as shown in Figure. 1.

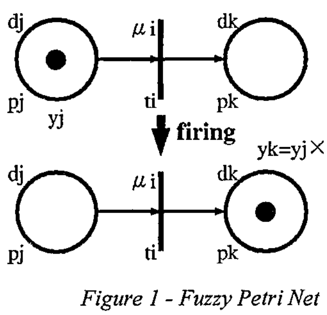

Figure 1 - Fuzzy Petri Net

Fuzzy Coloured Petri Nets

It is very efficient methods to make knowledge representation by FPNs. Therefore, its total net size becomes very large, and it becomes difficult to see the similarities and the differences among the individual subnets representing similar parts. To avoid this kind of problems we propose FCPNs that is combination of FPNs and Coloured Petri Nets (CPNs). [7]

Coloured Petri Net

Coloured Petri Nets are a class of high level Petri Nets that are more expressive and powerful than classical Petri Nets (place and transition nets). While classical Petri Nets model a system by the movement of single, untyped tokens around a net, Coloured Petri Nets allow complex data structures to be attached to tokens. This greatly improves expressiveness, while significantly reducing the size and complexity of the resulting net.

As an example consider the standard synchronization problem consisting of five philosophers two alternately think and eat. To eat, a philosopher needs two forks, but unfortunately there are only five forks nearest or him (see Figure 2). Obviously two neighbours cannot eat at the same time.

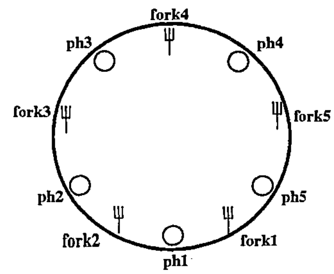

Figure 2 - Five dining philosophers.

The philosopher system can be described by PTNs. Its graphical representation is shown in Figure 3 ('th', 'e', and 'ff' are short for 'think', 'eat' and 'free forks', respectively).

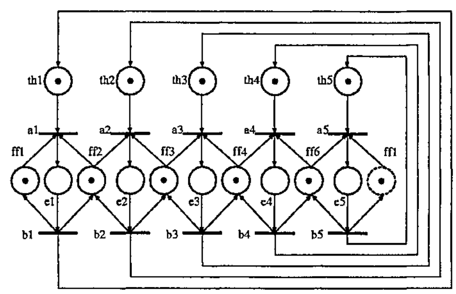

Figure 3 - Petri Nets describing the philosopher system. For convenience the place ff_1 has been drawn twice. It has only one token.

The first step will be to replace the five places th1, th2,...,, th5 by a single place 'think', which can carry up to five tokens. To distinguish between these tokens, which represent different philosophers, we attach to 'think' a set of colours ph, and we demand that all tokens on 'think' must be labelled by an element of ph.

Analogously the places e1, e2,..., e5 are replaced by a single place 'eat' with ph as the set of possible colours, and the places ff1, ff2, ff5 are replaced by a single place 'free forks' with f as the set of possible colours.

The next step will be to replaces the five transitions a1, a2,..., a5 by a single transition 'take forks', which may fire in five different ways corresponding to the five philosophers. To distinguish between these different ways of firings we attach to the transition 'take forks' the set of colours, ph, representing the individual philosophers.

Analogously we replace the transitions b1, b2,..., b5 by a single transition 'put down forks' with ph as the set of possible firing colours. We then get the Coloured Petri Nets in Figure 4, where by convention all unlabelled arcs represent the identity function of the set of colours attached to its transition.

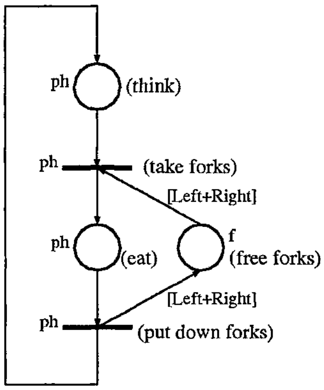

Figure 4 - Coloured Petri Nets describing the philosopher system.

Fuzzy Coloured Petri Net

The structure of FCPNs [8] depend on the rule-types of fuzzy production rules as FPNs. The composite fuzzy production rule can be distinguished into the following five rule-types, respectively.

Type 1:

IF d1j THEN d1k (CF=1i)

IF d2j THEN d2k (CF=2i)

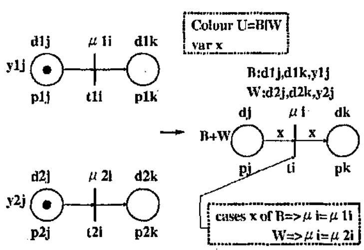

Figure 5 - The change to Fuzzy Coloured Petri Nets from Fuzzy Petri Nets with Type 1

Type 2:

IF d11 AND d12 (CF=1i)

IF d21 AND d22 (CF=2i)

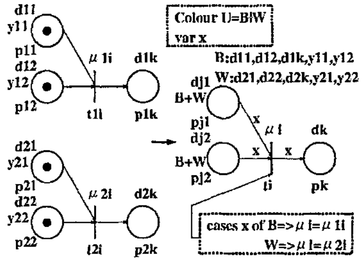

Figure 6 - The change to Fuzzy Coloured Petri Nets from Fuzzy Petri Nets with Type 2.

Type 3:

IF d1j THEN d11 AND d12 (CF=1i)

IF d2j THEN d21 AND d22 (CF=2i)

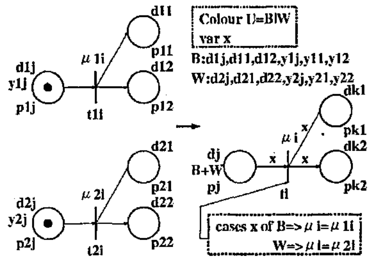

Figure 7 - The change to Fuzzy Coloured Petri Nets from Fuzzy Petri Nets with Type 3.

Type 4:

IF d11 OR d12 THEN d1k (CF=11,12)

IF d21 OR d22 THEN d2k (CF=21,22)

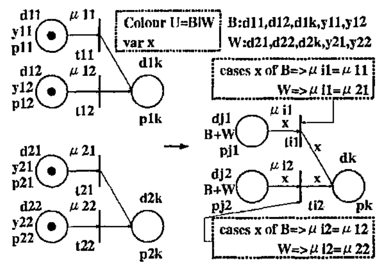

Figure 8 - The change to Fuzzy Coloured Petri Nets from Fuzzy Petri Nets with Type 4.

Type 5:

IF d1j THEN d11 OR d12 (CF=11,12)

IF d2j THEN d21 OR d22 (CF=21,22)

In each rule-types, it make its net structures change to FCPNs from FPNs, and it become such as Figure 5-8. However, the rule-type 5 are unsuitable for deducing control because they do not make specific implications. Therefore, we do not allow this type of rule to appear in the knowledge base. In following, we will not discuss this type of rule.

Maximum Value Representation with Fuzzy Coloured Petri Nets

In the rule-type 4, if it is equal the fellow input token colours and it is equal the value of the fellow certainty factors, its net structure is able to represent by writing 'MAX' on the arc expressions (see Figure 9.) Therefore, if the value of the fellow certainty factors is "1.00", its net structure is able to represent by writing 'MAX' on the transition expression (see Figure 10).

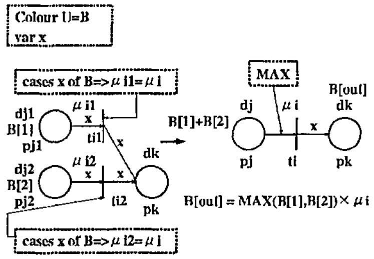

Figure 9 - 'MAX' representation 1 by Fuzzy Coloured Petri Nets

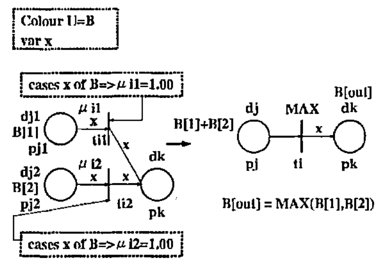

Figure 10 - 'MAX' representation 2 by Fuzzy Coloured Petri Nets.

Learning of Fuzzy Rules using Genetic Algorithms

If it construct inference engine using FPNs or FCPNs, the uncertainty in fuzzy production rule expand [2]. To control its, we may meet the relations among its fuzzy production rules are ambiguous. An algorithm is presented for checking the consistency of fuzzy knowledge base via a learning process using Genetic Algorithm (GA). [6] [7]

Leaning of Fuzzy Rules

A new type of inference engine using FPNs is proposed for reasoning under uncertainty. An Algorithm is presented for improving the fuzzy production rules to get a godd consistency of reasoning. The training process of improving rules is developed by GA.

Leaning of Fuzzy Rules using Genetic Algorithms

In the cases where implement inference engine using FPNs, the accuracy of fuzzy rules have the direct affect by the property. To avoid this problem, we propose the implementation of inference engine that included learning process using GA. We use this chromosome that is coding antecedent parts of rule and certainty factor of rule as shown in Figure 11. We are evolved its chromosome by genetic operator. We include roulette selection, elite preserving selection, uniform crossover and mutation for genetic operator.

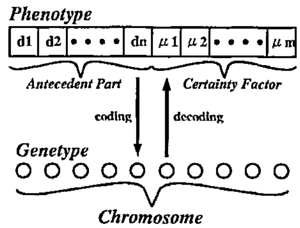

Figure 11 - Coding and Encoding of fuzzy production rules.

Application to Medical Diagnostics System

To verify the validity and the effectiveness of the proposed system, the system is applied to the medical diagnostic system for three diseases with 'intervertebral' that have the middle hypothesis as 'redicular pain'. FPN and FCPN as shown in Figure 12 and Figure 13, respectively can model the medical diagnostic system.

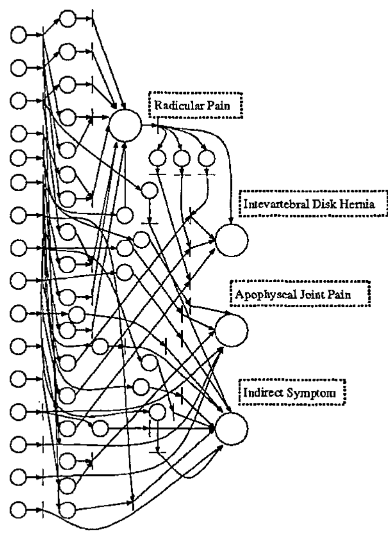

Figure 12 - Fuzzy Petri Net Model of the medical diagnostic system

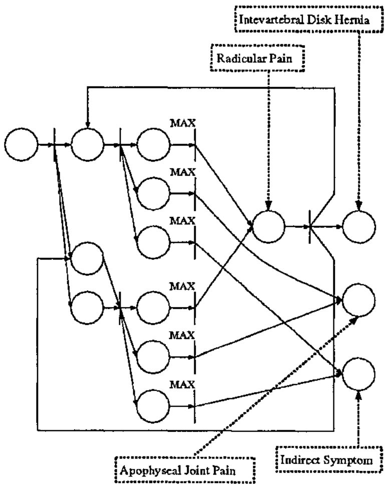

Figure 13 - .Fuzzy Coloured Petri Net Model of the medical diagnostic system.

In the FPN model, the comparatively large place is equivalent to each disease. The FCPN model can be expressive by using feedback-like the output of the middle hypothesis as the input of the next rule.

After we trained the network using GA, we have developed the diagnostic system correctly diagnosed 87.5% of all patient records.

Moreover, we compare the difference of complication between FPN and FCPN using its places, transitions and arcs as shown in Table 1.

Table 1 - The difference of complication between FPN and FCPN.

	FPN	FCPN	Reduction rate
Places	52	14	73.1 %
Transitions	40	10	75.0 %
Arcs	103	27	74.0 %

Furthermore, we compare the difference of computation time between FPN and FCPN using second time as shown in Table 2.

Table 2 - The difference of computation time between FPN and FCPN.

	FPN	FCPN	Reduction rate
Machine 1	649	594	8.5 %
Machine 2	1410	1282	9.1 %
Machine 3	2897	2618	7.7 %

Conclusion

In this paper, we have proposed a medical diagnostic system using FCPN and introduce the methods to learn the fuzzy production rules in the proposed nets with GA.

Using the method, we have successfully developed the medical diagnostic system for intervertebral diseases, which have the middle hypothesis. In the result, the proposed method cuts down the net size by approximately 74.0%, and cuts down the computation time by approximately 8.4%.

We can expect the more complicated and the larger becomes the size of system, the more effective for the model reduction and the saving of computation time.

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