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# Fuzzy Classification Rule Mining Based on Genetic Network Programming Algorithm

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***Abstract*—Association rule-based classification is one of the most important data mining techniques applied to many scientific problems. In the last few years, extensive research has been carried out to develop enhanced methods and obtained higher classification accuracies than traditional classifiers. However, the current studies show that the association rule-based classifiers may also suffer some problems inherited from association rule mining such as handling of (1) continuous data and (2) the support/confidence framework. In this paper, a novel fuzzy classification model based on Genetic Network Programming (GNP) that can deal with the above problems has been proposed. GNP is one of the evolutionary optimization algorithms that uses directed graph structures as solutions instead of strings (Genetic Algorithms) or trees (Genetic Programming). Therefore, GNP can deal with more complex problems by using the higher expression ability of graph structures. The performance of our algorithm has been compared with other relevant algorithms and the experimental results show the advantages and effectiveness of the proposed model.**

***Index Terms*—Association rule mining, fuzzy class association rules, classification, evolutionary computation, Genetic Network Programming.**

## I. INTRODUCTION

Related to the data mining field, classification is defined as the process to build a model in order to describe a data class or concept, in such a way to classify the data whose class is unknown into an appropriate data class [1]. One of the comprehensible models used is the association rule-based classification. A class association rule is generally expressed as a IF-THEN rule, in the following way: IF [*term*1 AND *term*2 AND ... ] THEN [class]. Each *term* of the antecedent is a pair of [attribute, value]. The rule consequent is the result of classification, that is, the class value of the attribute that belongs to. Conventional classification algorithms are based on heuristic search techniques and concentrate on finding a subset of the representative rules from the training data. These rule-based techniques can determine the classification usually fast but their accuracy generally are not good enough. Recently, extensive research has been carried out to develop enhanced methods and higher classification accuracy is obtained than traditional classifiers. However, the current studies show that association classifiers may also suffer some problems inherited from association rule mining such as handling of (1) continuous data and (2) the support/confidence framework.

In this paper, a Genetic Network Programming (GNP)-based data mining method has been proposed for discovering comprehensible fuzzy association rules, which is potentially useful for classification tasks. GNP is one of the evolutionary algorithms inspired by biological evolution. Thus, GNP is an extension of Genetic Algorithms (GA) and Genetic Programming (GP) [2], [3], [4], [5]. The reasons of selecting a GNP-based association rule mining method are described as follows [6]: (1) There is no need to encode the association rules into the genome of an individual in GNP. Thus, GNP-based association rule mining is a tool for extracting a large number of rules into a general pool. Whereas, other evolutionary techniques requires the encoding scheme of the individuals for representing rule sets. (2) GNP is able to extract a large number of rules without the bloating problem found in Genetic Programming. (3) Because of GNP's structure, the measurements such us support, confidence and $\chi^2$ of the rules, are easily calculated by GNP individuals [7]. (4) The genetic operators executed in GNP such as crossover and mutation allows the GNP-based association rule mining to find new rules according to the progress of evolution. In other words, due to the genetic operators of GNP individuals, new attributes are evaluated and new relationships between attributes are found in each generation, as a result, the new rules that satisfy the significance measures are mined. (5) According to the supervisor's requirements, GNP is able to mine an adequate number of rules through generations and store them in the general pool, this is because the rules extraction is done without identifing frequent itemsets like most Apriori-based data mining algorithms use, therefore, the GNP-based association rule mining method extracts important fuzzy rules for the user's purpose in a short time.

## II. FUZZY CLASSIFICATION RULE MINING BASED ON GENETIC NETWORK PROGRAMMING

In this section, the proposed GNP-based method is described for the fuzzy clasification task of data mining. The mined fuzzy class association rules have the following form of $IF$ [conditions] $THEN$:

If $(A_i\, is\, Q_i) \wedge \cdots \wedge (A_j\, is\, Q_j) \Rightarrow (C = k)$,

where, $Q_i, ..., Q_j$ are the linguistic terms of the fuzzy attributes $A_i, ..., A_j$ and $k$ denotes the class $(k = 0, 1, 2, ...K)$.

### A. Fuzzy Discretization Technique for Handling Continuous Attributes

Since the accuracy of a classification model can be largely affected by the partitioning of continuous attributes, a fuzzy discretization technique is proposed for dealing with databases with continuous data. Therefore, the values of all continuous attributes of the database are fuzzified into three linguistic terms (*e.g*. low, middle and high). These linguistic terms are defined by the combination of trapezoidal and triangular membership functions symmetrically spaced as shown in Fig. 1. Each continuous attribute is associated with its own membership functions [See Fig. 2]. In addition, the parameters of the membership functions are evolved generation by generation in order to discover more interesting rules. Non-uniform mutation [8] was used for the evolution of the parameters of the membership functions. This genetic operator which reduces the disadvantages of random mutation, allows shifting the coordinates of the trapezoid and triangular, performing a more global search in the space of candidate membership functions.

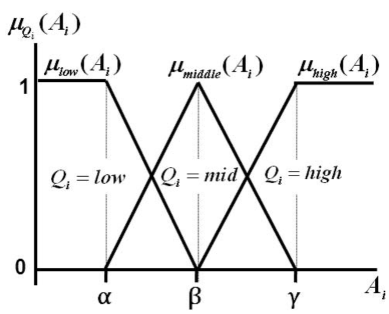
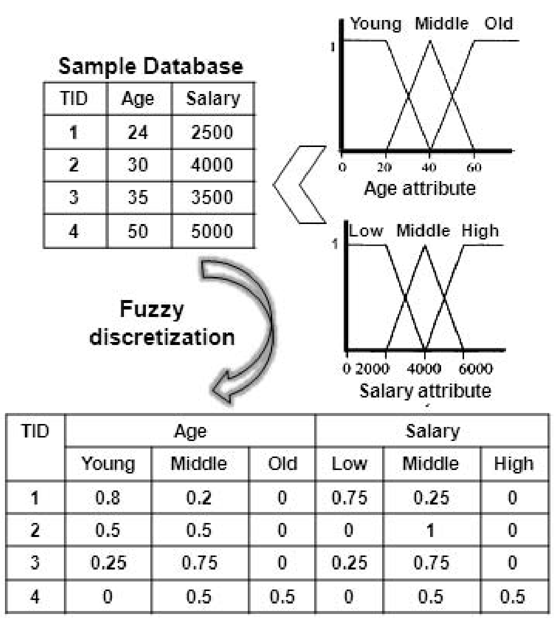



Fig. 1. Membership functions of Attribute $A_i$.




Sample Database

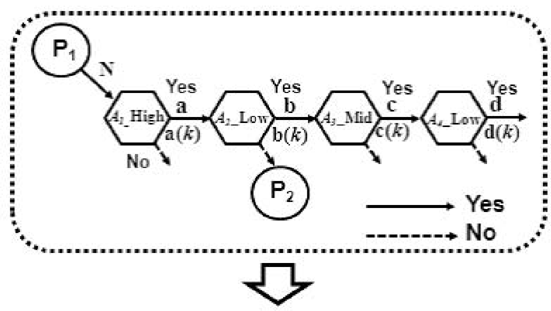
| TID | Age | Salary |
|---|---|---|
| 1 | 24 | 2500 |
| 2 | 30 | 4000 |
| 3 | 35 | 3500 |
| 4 | 50 | 5000 |

| TID | Age | | | Salary | | |
|---|---|---|---|---|---|---|
| | Young | Middle | Old | Low | Middle | High |
| 1 | 0.8 | 0.2 | 0 | 0.75 | 0.25 | 0 |
| 2 | 0.5 | 0.5 | 0 | 0 | 1 | 0 |
| 3 | 0.25 | 0.75 | 0 | 0.25 | 0.75 | 0 |
| 4 | 0 | 0.5 | 0.5 | 0 | 0.5 | 0.5 |

Fig. 2. Fuzzy attributes obtained from continuous databases.

### B. Transitions and Measurements using GNP

In this phase, the main task is to extract the fuzzy class association rules from a fuzzified training set using GNP individuals. The basic structure of GNP for fuzzy class association rule mining is shown in Fig. 3. The association rules are represented as the connections of judgment nodes in GNP. Each judgment node examines the fuzzy attribute values, which were calculated in the last subsection. $P_1$ is a processing node and is a starting point of extracting association rules. Each processing node has an inherent numeric order ($P_1$, $P_2$,. . . , $P_s$) and is connected to a judgment node [6]. Yes-side of the judgment node is connected to another judgment node. No-side of the judgment node is connected to the next numbered processing node. The calculation of the measurements such us support, confidence and $\chi^2$ is made using processing nodes [7]. Judgment nodes can be reused and shared with some other association rules because of GNP's features. All GNP individuals are searched in parallel at the same time. Once a GNP individual starts the searching for association rules, the fuzzy values are employed to determine the transition from one judgment node to another, that is, the fuzzy value is used for moving to the Yes-side or No-side of the judgment node. The transition from one judgment node to another can be determined probabilistically or deterministically.




$$(A_1\_High) \wedge (A_2\_Low) \wedge (A_3\_Mid) \wedge (A_4\_Low) \Rightarrow (C = k)$$
$$(k = 0, 1, \ldots, K)$$

Fig. 3. Basic GNP structure for fuzzy association rule mining.

*1) GNP with probabilistic transitions:* Fig. 4 and Fig. 5 show how the transition of nodes is done using probability $P_t$ determined by the fuzzy values. In Fig. 4, $r$ is a random variable in [0,1], $a_i$ is the value of fuzzy attribute $A_i$, $\mu_{Qi}(a_i)$ is the value of the membership function $\mu_{Qi}(A_i)$ when the value of fuzzy attribute $A_i$ is $a_i$. Therefore, a random number is generated and compared to the membership value of the fuzzy attribute. If the random number is smaller than or equal to the membership value, then go to the Yes-side of the judgment node, otherwise, go to the No-side of the jugdment node.

*2) GNP with deterministic transitions:* Fig. 6 shows an example of the deterministic transition of nodes using the fuzzy values. If the membership value of the fuzzy attribute is greater than or equal to the membership values of all other linguistic terms of the fuzzy attribute, then go to the Yes-side of the judgment node, otherwise, go to the No-side of the jugdment

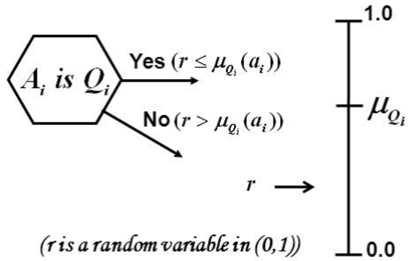



Fig. 4. Probabilistic transition from one judgment node to another.

| TID | $A_1$ | | | $A_2$ | | | $A_3$ | | | $A_4$ | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | Mid | High | Low | Mid | High | Low | Mid | High | Low | Mid | High |
| 1 | 0 | 0.2 | **0.8** | **0.5** | 0.5 | 0 | 0.6 | **0.4** | 0 | **0.6** | 0.4 | 0 |
| 2 | 0 | 0.3 | **0.7** | **0.4** | 0.6 | 0 | 0.2 | **0.8** | 0 | **0.2** | 0.8 | 0 |
| 3 | 0 | 0.5 | **0.5** | **0.3** | 0.7 | 0 | 0 | **0.3** | 0.7 | **0.4** | 0.6 | 0 |
| 4 | 0 | 0.4 | **0.6** | **0.1** | 0.9 | 0 | 0.7 | **0.3** | 0 | **0.5** | 0.5 | 0 |

**Fuzzy values are used as the probability $P_t$ moving to the Yes-side.**

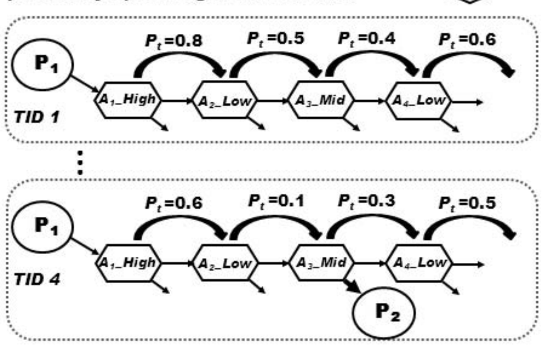



Fig. 5. Transition from one judgment node to another using probability $P_t$ determined by fuzzy values.

node.

*3) Calculation of measurements using GNP:* In order to calculate the support, confidence and $\chi^2$ of the fuzzy rules, the total number of tuples moving to Yes-side at each judgment node is calculated for every processing node [7]. In Fig. 3, $N$ is the total number of tuples and $a$, $b$, $c$ and $d$ are the number of tuples moving to Yes-side at each judgment node. These counts are used for the calculation of the measurements. Table I shows how to calculate the support and confidence of the fuzzy rules extracted from the GNP individual in Fig. 3.

TABLE I
SUPPORT AND CONFIDENCE OF FUZZY RULES.

| association rules | support | confidence |
|---|---|---|
| $A_1\_High \Rightarrow A_2\_Low$ | b/N | b/a |
| $A_1\_High \Rightarrow A_2\_Low \wedge A_3\_Mid$ | c/N | c/a |
| $A_1\_High \Rightarrow A_2\_Low \wedge A_3\_Mid \wedge A_4\_Low$ | d/N | d/a |
| $A_1\_High \wedge A_2\_Low \Rightarrow A_3\_Mid$ | c/N | c/b |
| $A_1\_High \wedge A_2\_Low \Rightarrow A_3\_Mid \wedge A_4\_Low$ | d/N | d/b |
| $A_1\_High \wedge A_2\_Low \wedge A_3\_Mid \Rightarrow A_4\_Low$ | d/N | d/c |

| TID | $A_1$ | | | $A_2$ | | | $A_3$ | | | $A_4$ | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Low | Mid | High | Low | Mid | High | Low | Mid | High | Low | Mid | High |
| 1 | 0 | 0.2 | **0.8** | **0.5** | 0.5 | 0 | 0.6 | **0.4** | 0 | **0.6** | 0.4 | 0 |
| 2 | 0 | 0.3 | **0.7** | **0.4** | 0.6 | 0 | 0.2 | **0.8** | 0 | **0.2** | 0.8 | 0 |
| 3 | 0 | 0.5 | **0.5** | **0.3** | 0.7 | 0 | 0 | **0.3** | 0.7 | **0.4** | 0.6 | 0 |
| 4 | 0 | 0.4 | **0.6** | **0.1** | 0.9 | 0 | 0.7 | **0.3** | 0 | **0.5** | 0.5 | 0 |

**The transition from one judgment node to another is possible if the fuzzy value is ≥ 0.5.**

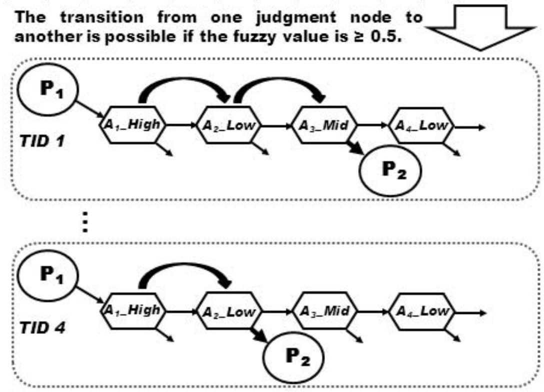



Fig. 6. Deterministic transition from one judgment node to another.

### *C. The GNP-based Fuzzy Class Association Rule Mining Algorithm*

Therefore, we describe the algorithm for discovering fuzzy class association rules from continuous data in the case of a probabilistic transition.

INPUT: A dataset with $n$ continuous attribute values, a set of fuzzy membership functions $\mu_{Qn}(A_n)$, a predefined number of generations $m$, a predefined minimum support ($sup_{min}$), minimum confidence ($conf_{min}$) and $\chi^2_{min}$ thresholds.

OUTPUT: A pool of fuzzy class association rules with support, confidence and $\chi^2$ values larger than or equal to the predefined minimum support, minimum confidence and $\chi^2$ thresholds.

$STEP$ 1: Fuzzify each continuous attribute of the dataset into three linguistic values, $e.g.$ low, medium and high. Each continuous attribute is associated with its own membership function.

$STEP$ 2: Randomly generate a population of GNP individuals with a predefined number of judment and processing nodes.

$STEP$ 3: Extract fuzzy class association rules using GNP as follows:

$STEP$ 3.1: Evaluate if a fuzzy attribute is high, medium or low using judgment nodes by the following: the transition from one judgment node to another is executed using the membership values. Concretely, a random number in [0.1] is generated and compared to the fuzzy membership value. If the random number is smaller than or equal to the fuzzy membership value, then go to the Yes-side of the judgment node, otherwise, go to the No-side of the judgment node.

$STEP$ 3.2: Calculate the support, confidence and $\chi^2$ of the fuzzy class association rule by counting the total number of tuples moving to Yes-side at each judgment node using the processing nodes.

*STEP* 4: Store the fuzzy class association rules that satisfy the minimum support, confidence and $\chi^2$ thresholds.

*STEP* 5: Check whether an important rule is new or not (whether it is already in the pool or not) as follows:

*STEP* 5.1: If the fuzzy rule is new, store it in the pool with its *support*, *confidence*, $\chi^2$ and the parameters of the fuzzy membership functions.

*STEP* 5.2: If the fuzzy rule in not new, for example, it has the same fuzzy attributes with different fuzzy membership functions, then store the fuzzy rule with higher $\chi^2$ value. Therefore, the pool is updated in every generation and only the important fuzzy rules with higher $\chi^2$ values along with adapted fuzzy parameters are stored.

*STEP* 6: If the number of generations $m$ reaches, then stop the algorithm, otherwise go to the next step.

*STEP* 7: Perform the evolution of the GNP individuals as follows:

*STEP* 7.1: Calculate the fitness of each GNP individual by:

$$F = \sum_{r \in R} \{\chi^2(r) + 10(n(r) - 1) + \alpha_{new}(r)\}, \tag{1}$$

where,

$R$: set of suffixes of extracted important association rules satisfying (3), (4) and (5) in a GNP individual

$\chi^2(r)$: $\chi^2$ value of rule $r$.

$n(r)$: the number of attributes in the antecedent of rule $r$.

$\alpha_{new}(r)$: additional constant defined by

$$\alpha_{new}(r) = \begin{cases} \alpha_{new} & \text{(rule } r \text{ is new)} \\ 0 & \text{(rule } r \text{ has been already extracted)} \end{cases} \tag{2}$$

*STEP* 7.2: Select the top $1/3$ GNP individuals according to their fitness values.

*STEP* 7.3: Execute the genetic operators to the selected GNP individuals in order to create the next population as follows: (1) Crossover: Two offspring is produced from parents. Uniform crossover is used. Judgment nodes are selected as crossover nodes with the probability of $P_c$. (2) Mutation-1: The connection of the judgment nodes is changed by mutation rate of $P_{m1}$. (3) Mutation-2: The function of the judgment nodes is changed by mutation rate $P_{m2}$.

*STEP* 8: Evolve the parameters of the fuzzy membership functions using non uniform mutation [8]. Since the combination of two trapezoidal and one triangular membership functions spaced symmetrically is used, the number of parameters for evolution is three: $\alpha$, $\beta$ and $\gamma$ [See Fig. 2]. These parameters are predefined only for the first generation and from the second generation, $\alpha$ and $\beta$ evolve by non-uniform mutation and $\gamma$ is automatically calculated by ($2\beta$ - $\alpha$) in order to maintain the parameters symmetrically spaced.

*STEP* 9: Go to *STEP* 1.

### D. Building a Classifier Model

For each test data, the classifier computes the average matching degree between data $d$ and the rules in class $k$. Since every fuzzy rule is stored in the pool with its own fuzzy parameters, the attributes of data $d$ have to be fuzzified according to the fuzzy parameters of rule $r$. Then, the rules in the pool are used to predict the class of data $d$. Finally, the class with the highest average matching degree is assigned to the test data. The accuracy rate on the test set is computed as the number of correctly classified test samples divided by the total number of test samples.

Therefore, the classification of test data $d$ is determined as follows:

1) $R_k$: Set of suffixes of rules in class $k$, $(k = 0, 1, 2 \ldots K)$.

2) $m_k(d)$: Compute the average matching degree between data $d$ and the rules in class $k$.

$$m_k(d) = \frac{1}{|R_k|} \sum_{r \in R_k} Match_k(d, r), \tag{3}$$

$$Match_k(d, r) = \frac{N_k(d, r)}{N_k(r)}, \tag{4}$$

where,

$Match_k(d, r)$ : matching degree between data $d$ and rule $r$ in class $k$.

$N_k(d, r)$ : the sum of the fuzzy membership values of the fuzzy attributes in the antecedent of fuzzy rule $r$ in class $k$, which are calculated by data $d$.

$N_k(r)$: the number of attributes in the antecedent of rule $r$ in class $k$.

3) Predict in such way that data $d$ belongs to the class having the highest $m_k(d)$.

## III. Simulation Results

To evaluate the accuracy and performance of the proposed classifier based on Genetic Network Programming, eight public-domain datasets from UCI (University of California at Irvine) dataset repository have been selected [9]. Table II describes the datasets along with some related statistical information. There are two reasons why these eight classification problems were selected. First of all, the datasets are multiclass pattern classification problems involving continuous attributes. Secondly, we want to compare the proposed method to the existing algorithms. We randomly select 80% of the records of the database as the training set and 20% of the records are used for the test set. In terms of the classification accuracy, we compared the performances of the proposed model with three other evolutionary systems described in the literature: CEFR-MINER [10], ESIA [11], BGP [12] and three Apriori-like mining methods described in [13]. For the GNP-based class association rule mining algorithm, the number of GNP individulas in the population is 120. The number of processing and judgment nodes are 20 and 200, respectively. We use $\chi^2_{min}$ = 6.63, $sup_{min}$ = 0.01 and $\alpha_{new} = 150$. The probability of crossover is $P_c = 1/5$, mutation of the connection is $P_{m1} = 1/3$ and mutation of the function is $P_{m2} = 1/5$. All algorithms has been developed in a Java-based software development environment. Experiments were performed on a 1.50GHz Pentium M with 504MB RAM.

TABLE II
UCI ML DATASETS USED IN THE EXPERIMENTS [9].

| Datasets | Size | # Attribute | # Class |
|---|---|---|---|
| Heart | 303 | 15 | 2 |
| Ionosphere | 351 | 34 | 2 |
| CRX | 690 | 15 | 2 |
| Iris | 150 | 5 | 3 |
| Glass | 214 | 11 | 7 |
| Pageblocks | 5473 | 11 | 5 |
| Waveform | 5000 | 22 | 3 |
| Pima | 768 | 9 | 2 |

In order to obtain the best performance of the proposed algorithm, the following methods were tested:

- Probabilistic transitions in GNP individuals with and without evolution of the fuzzy membership functions.
- Deterministic transitions in GNP individuals with and without evolution of the fuzzy membership functions.

The number of extracted fuzzy rules and the classification accuracies are explained for the eight datasets. Fig. 7 and Fig. 8 show the total number of fuzzy rules extracted when the maximun number of generations is set to 100, while Fig. 9 and Fig. 10 show the classification accuracy. In these figures, $C1$ indicates *with evolution of the fuzzy membership functions*, while $C2$ indicates *without the evolution of the fuzzy membership functions*. It can be seen from Fig. 7 and Fig. 8 that GNP with probabilistic transitions considerably extracts more rules than GNP with deterministic transitions. This is because, GNP with probabilistic transitions has probabilistics natures, *i.e.*, it has the possibility to produce many types of rules. Whereas, GNP with deterministic transitions extract more general rules because it has no chance to produce the exceptional rules. Fig. 11 shows the classification accuracy of the different proposed methods.

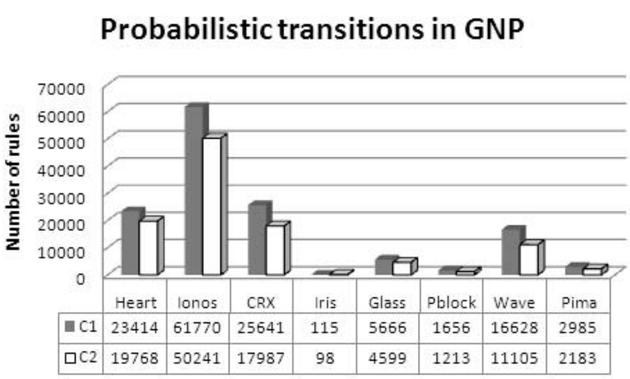



Fig. 7. Number of extracted fuzzy rules by GNP with probabilistic transitions.

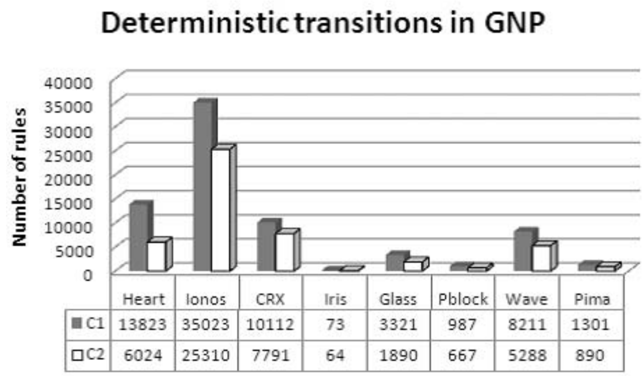



Fig. 8. Number of extracted fuzzy rules by GNP with deterministic transitions.

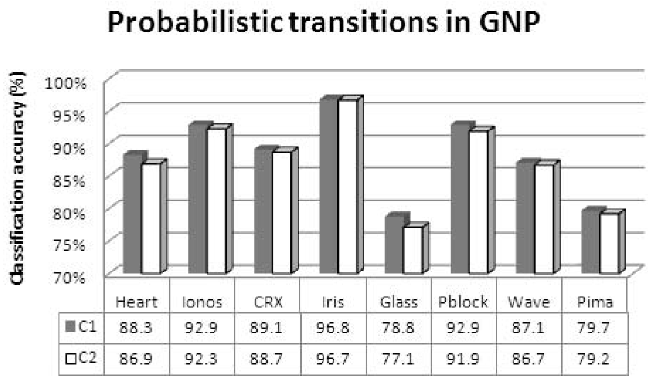



Fig. 9. Classification accuracies by GNP with probabilistic transitions.

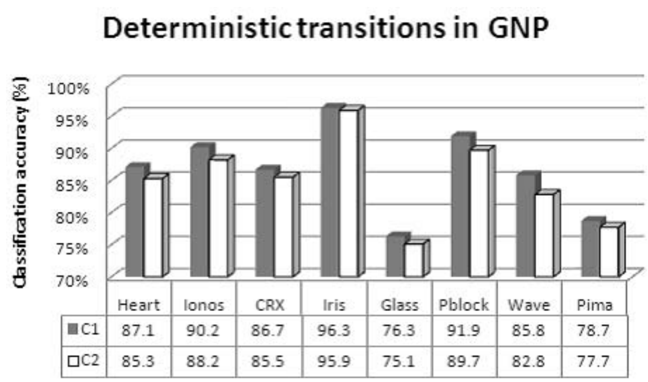



Fig. 10. Number of extracted fuzzy rules by GNP with deterministic transitions.

As can be seen from Fig. 11, probabilistic transitions in GNP with the evolution of the fuzzy membership functions obtain the highest classification accuracy. Thus, Table III shows the classification accuracy of seven methods including the proposed best one on the eight datasets listed in Table II. If there is no available published results, the symbol "-" is placed. It can be seen from Table III that the proposed GNP-Fuzzy with probabilistic transitions method considerably outperforms all the other methods. A deeper analyses of the obtained results

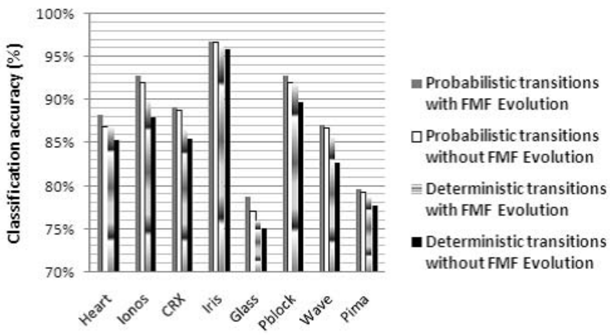



Fig. 11. Classification accuracies by probabilistic/deterministic transitions and with/without the evolution of the fuzzy membership functions.

are studied as follows:

- Fig. 7 and Fig. 8 show that the proposed method can extract a large amount of interesting fuzzy rules for the selected databases, this is because the GNP individuals are used to extract the fuzzy rules and jugment nodes can be reused and shared with some other association rules because of GNP's structure.
- It is easy to compute the membership values, however the critical task is to find an appropiate membership functions. This is achieved by evolving the fuzzy parameters using non-uniform mutation. Fig. 11 indicates that the evolution of the fuzzy membership functions shows the effectiveness for discovering new fuzzy rules generation by generation. This leads to the improvement of the classification accuracy.
- The other conventional methods obtained lower classification accuracy, because it is generally difficult for them to deal with a large number of continuous attributes in the dataset. For instance, the evolutionary algorithm described in paper [10], has the difficulty in coping with such a relatively good number of attributes being fuzzified.
- The achieved accuracy reveals the effectiveness of the proposed fuzzy class association rule mining and classification. We consider these results are very promising, taking into account that the proposed model mines fuzzy rules which are more understable for the examiners.

TABLE III
COMPARISON OF THE CLASSIFICATION ACCURACY (%).

| Dataset | GNP | CERF | ESIA | BGP | CMAR | C4.5 | CBA |
|---|---|---|---|---|---|---|---|
| Heart | **88.3** | 82.2 | 74.4 | - | 82.2 | 81.9 | 82.2 |
| Ionosphere | **92.9** | 88.6 | - | 89.2 | 91.5 | 90.0 | 92.3 |
| CRX | **89.1** | 84.7 | 77.3 | - | 84.9 | 84.9 | 84.7 |
| Iris | **96.8** | 95.3 | 95.3 | 94.1 | 94.0 | 95.3 | 94.7 |
| Glass | **78.8** | - | 72.4 | - | 70.1 | 68.7 | 73.9 |
| Pageblocks | **92.9** | - | - | - | - | 89.6 | - |
| Waveform | **87.1** | - | - | - | 83.2 | 78.1 | 80.0 |
| Pima | **79.7** | - | 70.18 | 72.5 | 75.1 | 75.5 | 72.9 |

## IV. CONCLUSION

In this paper, a classification method based on fuzzy classification rules using GNP has been proposed. We have shown that the GNP's characteristic makes the proposed model easy to formulate and use. Taking the GNP's structure into account, the extraction of fuzzy association rules is done without identifying frequent itemsets used in most Apriori-based data mining algorithms. Calculation of the support, confidence and $\chi^2$ values is done in order to measure the significance of the rules. The fuzzy membership values are used for fuzzy rules extraction, where the parameters of the membership functions are evolved by non-uniform mutation in order to perform a more global search in the space of candidate membership functions. The performances of the proposed algorithm were compared with other relevant algorithms and the experimental results have shown the advantages and effectiveness of the proposed model.

## REFERENCES

[1] J. Han and M. Kamber, "Data Mining: Concepts and Techniques", Department of Computer Science, University of Illinois at Urbana Champaign, pp. 4, 2006.
[2] S. Mabu, K. Hirasawa and J. Hu, "A Graph-Based Evolutionary Algorithm: Genetic Network Programming and Its Extension Using Reinforcement Learning", Evolutionary Computation, MIT press, Vol. 15, No.3, 2007.
[3] K. Hirasawa, M. Okubo, H. Katagiri, J. Hu and J. Murata, "Comparison between Genetic Network Programming and Genetic Programming", In Proc. of the Congress of Evolutionary Computation, pp.1276-1282, 2001.
[4] T. Eguchi, K. Hirasawa, J. Hu and N. Ota, "A Study of Evolutionary Multiagent Models Based on Symbiosis", IEEE Trans. on Systems, Man and Cybernetics - Part B -, Vol. 36, No. 1, pp. 179-193, 2006.
[5] K. Hirasawa, T. Eguchi, J. Zhou, L. Yu, S. Markon, "A Double-Deck Elevator Group Supervisory Control System Using Genetic Network Programming", IEEE Trans. on Systems, Man and Cybernetics, Part C, Vol. 38, No. 4, pp. 535-550, 2008.
[6] K. Shimada, K. Hirasawa and J. Hu, "Genetic Network Programming with Acquisition Mechanisms of Association Rules", Journal of Advanced Computational Intelligence and Intelligent Informatics, Vol. 10, No. 1, pp.102-111, 2006.
[7] K. Shimada, K. Hirasawa and J. Hu, "Class Association Rule Mining with Chi-Squared Test Using Genetic Network Programming", In Proc. of the IEEE SMC, pp.5338-5344, 2006.
[8] Z. Michalewicz, "Genetic Algorithms + Data Structures = Evolution Programs", (3rd Edition), Springer, 1996.
[9] C. J. Merz and P. Murphy, UCI repository of machine learning database, http://www.cs.uci.edu/mlearn/MLRepository.html, 1996.
[10] R. Mendez, F. Voznika, A. Freitas and J. Nievola, "Discovering Fuzzy Classification Rules with Genetic Programming and Co-Evolution", In Proc. of the 5th European Conference on Principles of Data Mining and Knowledge Discovery (PKDD 2001), L N A I 2168, pp. 314-325, Springer Berlin, 2001.
[11] J. J. Liu and J. T. Kwok, "An Extended Genetic Rule Induction Algorithm", In Proc. of the Congress on Evolutionary Computation, La Jolla, CA, USA, July 2000.
[12] S. E. Rouwhorst and A. P. Engelbrecht, "Searching the Forest: Using Decision Tree as Building Blocks for Evolutionary Search in Classification", In Proc. of the Congress on Evolutionary Computation, La Jolla, CA, USA, pp. 633-638, 2000.
[13] X. Yin and J. Han, "CPAR: Classification based on Predictive Association Rules", In Proc. of the SIAM International Conference on Data Mining, 2003.