International Journal of Multimedia and Ubiquitous Engineering
Vol.10, No.8 (2015), pp.35-44
http://dx.doi.org/10.14257/ijmue.2015.10.8.04

A Novel Intelligent Fault Diagnosis Method and Its Application

Jing-Hua Zhu

Department of Computer Science, Wenzhou Vocational & Technical College, Wenzhou 325035, PR China

Abstract

In order to improve fault diagnosis precision and decrease misinformation diagnosis, rough set theory(RST) and RBF neural network (RBFNN) are introduced to overcome respective deficiency in order to propose a novel intelligence fault diagnosis(NCIRRFD) model and method in this paper. In this NCIRRFD method, the RST as a new mathematical tool is used to process inexact and uncertain knowledge in order to reduce decision tables for obtaining the minimum fault characteristic subset. At the same time, RST is used to serve for pretreatment data so that RBFNN structure is simplified and learning efficiency is improved in order to get an optimized NCIRRFD model for solving the inference complexity. An actual application case is selected to test and verify the proposed NCIRRFD method. The applied results show that the proposed NCIRRFD method can effectively eliminate false and improve the diagnostic accuracy.

Keywords: *Intelligent fault diagnosis, Rough set theory, RBF neural network, Knowledge discovery, Optimization*

1. Introduction

Fault is regarded as critical conditions or abnormal situations in the modern society. It is a range of abnormal operating states that are beyond a normal state, but fall short of automated shutdowns. And these conditions are the consequences of combinations of events that unexpectedly take place at the same time. Faults are also understood as any kind of fault in the actual dynamic running system. The faults could result from process variables, process components, or even basic control systems [1-2]. The efficient and accurate fault diagnosis is important for improving reliability and performance. It plays an important role in the operation and maintenance of the actual dynamic running system, which can not only reduce or eliminate the accident, but also bring the applied potential and reduce expenditure. The fault diagnosis began in the early 1970s and has been receiving more and more attention in the past two decades [3]. The increasing interests are applied for two major applications: academic research and industrial application due to safety-related matters.

Various fault diagnosis techniques and methods have been proposed for finding exact fault sections and fault components [4], among the Logical Reasoning (LR), Artificial Neural Networks (ANN), Expert System (ES), Rough Set Theory (RST), Fuzzy Theory (FT), Petri Net, Genetic Algorithm (GA) and other new algorithms. Lunzea and Schiller [5] proposed an example of an application of qualitative model-based diagnosis. The approach here is based on a probabilistic logic model. Assertions about signals are represented by logical propositions, and the model consists mainly of conditional probabilities of the form P. Tayarani-Bathaie *et al.* [6] proposed a neural network-based fault detection and isolation scheme to detect and isolate faults in a highly nonlinear dynamics of an aircraft jet engine. Towards this end, dynamic neural networks (DNN) are first developed to learn the input–output map of the jet engine. A number of simulation

ISSN: 1975-0080 IJMUE

studies are carried out to demonstrate and illustrate the advantages, capabilities, and performance of our proposed fault diagnosis scheme. Ma *et al.* [7] proposed a novel Multi-BP expert system (MBPES) method based on dividing the whole networks into many sub-BP groups within a short depth for power system fault diagnosis. The real power system data sets to test the effectiveness of MBPES. Experimental results show that MBPES obtains higher accuracy than two commonly used methods. Muralidharan and Sugumaran [8] proposed the rough set based rule learning and fuzzy classification of wavelet features for fault diagnosis of monoblock centrifugal pump. Rough set is used for feature extraction and fuzzy logic is used for classification. Escobet *et al.* [9] proposed a fault diagnosis methodology termed Visual Block-Fuzzy Inductive Reasoning, *i.e.* VisualBlock-FIR, based on fuzzy and pattern recognition approaches is presented and applied to PEM fuel cell power systems. Mansour *et al.* [10] proposed a simplified fault diagnosis method based on Petri nets to estimate the faulty item/section(s) of a large power generation station. The Petri nets are used as a modeling tool to build fault diagnosis models of item/section(s) of power station which aim to diagnose accurately the faults when large amount information of SCADA system is detected in the control room. Luo *et al.* [11] proposed a new module level fault diagnosis method for analog circuits. The results show that the proposed method is effective to identify system parameters and locate module level faults. Wu [12] proposed a fault diagnosis method based on wavelet v-support vector classifier machine and particle swarm optimization. The results of application in fault diagnosis of car assembly line show the hybrid diagnosis model based on RWv-SVC and PSO is effective and feasible. Diego *et al.* [13] proposed an automatic bearing fault diagnosis based on one-class ν-SVM. In order to check the performance of the method, two different data sets are used. The results showed that the method was able not only to detect the failure in an incipient stage but also to identify the location of the defect and qualitatively assess its evolution over time.

In these methods, RBFNN has greater advantages in self-learning and knowledge acquisition, but it is difficult convergence, determination of the network parameters like hidden units, layers, learning rate and momentum value for training process of network [14]. In addition, when any configuration of the system changes, the related RBFNN needs to be re-trained. RST can effectively explain the significance of different attributes in knowledge expression system and in reduction of knowledge expression space. However, it is often helpless when it is used to deal with incomplete data. In order to simplify RBFNN structure and improve its anti-interference ability, RST is used to act as the pretreatment cell of RBFNN and mine knowledge from diagnosis knowledge base. Clearly, the synthesized method has better characteristics than single RBFNN or RST. So a novel intelligence fault diagnosis (NCIRRFD) model and method is proposed to overcome respective deficiency. An actual application case is selected to test and verify the proposed NCIRRFD method.

2. Rough Set Theory and RBF Neural Network

2.1. Rough Set Theory

Rough Sets Theory (RST) was proposed in 1982 by Pawlak in 1982 [15]. RST is a new mathematical tool, which process the imprecise, incomplete and uncertain data. The features of RST: though the data with uncertain, imprecise and noisy, and lack prior knowledge, it still obtained the concept classification rule by reduction attributes under keeping the classification capacity. After more than 20 years, it has been widely applied in those fields such as pattern recognition, decision analysis, approximate reasoning, machine learning, process control and knowledge discovery, *etc*.

In the RST, the knowledge is represented by the form of information system. An information system is a data set which expresses with the two-dimensional form. Row expresses the attribute and column expresses the object. In order to realize the processing data, there need some signs which to express knowledge. The knowledge expression is to research the set of objects. So the foundation of RST is its basic concept, and then a few main concepts are introduced as follow:

Def. 1 (Decision Table): Let an information system $S=\{U,A,V,F\}$,where U is a non-empty finite set of objects called the universe, $A=C\cup D$ is a non-empty finite set of attributes, C denotes the set of condition attributes and D denotes the set of decision attributes, $C\cap D=\phi$ .Each attribute $a\in A$ is associated with a set V_a of its value, which designates each object x attribute value in U , called the domain of a .

Def. 2 (Upper and Lower Approximations)**:** Let an information system $S=\{U,A,V,F\}$, $B\subseteq A$ and $X\subseteq U$, then the *B-lowe*r and *B-upper* approximations of X are defined, respectively, as follows:

$$\underline{R}(X)=\{\ x|x\in U:[x]_R\subseteq X\ \} \tag{1}$$

$$\overline{R}\ (X)=\{\ x|x\in U \text{ and } [x]_R\cap X\neq\phi\ \} \tag{2}$$

Clearly, $\underline{R}(X)$ consists of all objects in U that certainly belongs to X and $\overline{R}$ *(X)* consists of all objects in *U* that possibly belongs to *X* under the equivalence relation *R*. A rough set in *K* is the group of subsets of *U* with the same upper and lower approximations. The area of uncertainty or boundary region is defined as:

$$BNR(X)=\ \overline{R}\ (X)-\underline{R}(X). \tag{3}$$

Def. 3 (Indiscermibility Relation): Let an information system $S=\{U,A,V,F\}$, $B\subseteq A$ is a subset of attributes. The indiscernibility relation, denoted by *IND (B)* is an equivalence relation on the set *U* defined as:

$$IND\ (B)=\{(x,y)\in U\times U\mid\ \forall A\in B,\ a(x)=f(y)\ \} \tag{4}$$

Where *a(x)* denotes the value of attribute a objects *x*. For $B\subseteq A$, the relation *IND (B)* constitutes a partition of U, which is denoted by *U=U/ IND (B)* or just *U/B*.

Def. 4 (Object Set): Let an information system $S=\{U,A,V,F\}$, *A=CUD* and $B\subseteq C$. Define the *B* positive region of *D*:

$$PosB(D)=\cup\{B(X):X\in IND(D)\}. \tag{5}$$

PosB (D) is an object set which consists of the determinate *IND(D)* classes by using classified *IND(B)* for expressing the knowledge in the domain.

Def. 5 (Attribute Set): Let an information system $S=\{U,A,V,F\}$, *A=CUD* and the dependability between D and C is defined:

$$K=\gamma c(D)=|\ POS_C\ (D)|\ /\ |U|\ \ (0\leq K\leq 1) \tag{6}$$

For the attribute $c\in C$, if $\gamma_C\ (D)=\gamma_{C-c}\ (D)$, attribute *c* is redundant attribute to decision attribute *D*. Otherwise, *c* is indispensable attribute. The importance is defined:

$$S_{SGF}(c,C,D)=\gamma_C(D)-\gamma_{C-c}(D) \tag{7}$$

If any attribute in C is indispensable to decision attribute D, condition attribute C is independent of decision attribute D.

Def. 6 (Attribute Reduction): Let an information system $S=\{U,A,V,F\}$, *A=CUD* and $B\subseteq C$. If *B* is independent of *D*, and $\gamma_C\ (D)=\gamma_B\ (D)$, *B* in *C* is called relative reduction of D, and called $R_{red}\ (C)$. In general, the set of all indispensable relations in C will be called the core of C, and will be denoted as $C_{core}(C)$. Clearly, $C_{core}(C)=\cap\ R_{red}\ (C)$, where $R_{red}\ (C)$ is the family of all relations of *C*.

The core is indispensable knowledge features set in attribute sets. If any attribute in the core is eliminated, the classification ability of the whole knowledge system would descend.

2.2. RBF Neural Network

Artificial neural network is a new artificial intelligence technology with general application and great potential, which is composed of a large number of nerve cells. It offers significant support in terms of organizing, classifying, and summarizing data. ANN usually consists of an input layer, a hidden layer and an output layer. The input layer is represented by circles and behaves as a buffer. Each neuron receives multiple inputs from other neurons, except the neurons in the input layer, in proportion to their connection weights and then generates a single output in accordance with an activation function. An activation function can be linear or nonlinear form depending on applications. Training network consists of adjusting weights of the network using a different learning algorithm.

The training speed and real-time of the network more adaptable to fault diagnosis are considered in here. Due to the faults of BP networks such as slow learning speed and easy going into local infinitesimal values, RBF neural network (RBFNN) is applied to implement fault diagnosis. RBFNN belongs to multi-layer forward neural networks, and is composed of three parts respectively called input layer, hidden layer and output layer as shown in Figure. 1.

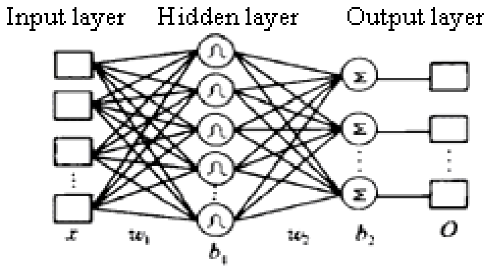

Figure 1. RBF Neural Network Structure

Known from Figure 1. while input learning vector of the neural network is $x=\{x_1,x_2,...,x_n\}^{\mathrm{T}} \in \mathrm{R}^{\mathrm{n}}$, the output of the neuron k in output layer can be expressed as

$$f(x)=\sum_{i=1}^{m} w_i \phi(x,c_i) \qquad (8)$$

Where x n-dimension input vector; $\phi(x,c_i)$ is basis function, and also is the output of the neuron i in hidden layer. $f(x)$ is output vector; ϕ is radial basis function; c_i is the centre of the i-th basis function, which has same dimensions as x; $w=\{w_1,w_2,...,w_m\}^{\mathrm{T}}$ $\in \mathrm{R}^{\mathrm{m}}$ is output weight matrix; m is the number of the neuron in input layer, n is the number of the neuron in hidden layer and k is the number of the neuron in output layer. Set Gauss function acts as basis function, then

$$\phi(x,c_i)=\exp\left(\frac{-\|\mathrm{x}-\mathrm{c_i}\|^2}{2\sigma_i^{\,2}}\right) \qquad (9)$$

Where σ_i expresses the variance of Gauss samples. Learning algorithm of RBFNN adopts a novel dynamic nearest neighbor-Clustering algorithm. The algorithm yields the least nodes and high learning speed. The key problem of RBFNN is to confirm the number of hidden nodes and the locations and width of corresponding center nodes. When they are confirmed, RBFNN from input to output will become linear equations. At the same time, output weight vector can be obtained by the least square method.

3. An Intelligent Fault Diagnosis Method

In the past decades, various fault diagnosis techniques have been proposed, but each method possesses stronger diagnosis ability for small-scale information system. For the large-scale information system, each existed fault diagnosis method still cannot effectively achieve fault diagnosis. RST can effectively elucidate the significance of different attributes in knowledge expression system and reduction of knowledge expression space. But it is often helpless when it is used to deal with incomplete data. RBFNN has greater advantages in self-learning and knowledge acquisition. But the training process of network is difficult convergence, and determination of the network parameters like hidden units, layers, learning rate and momentum value. In order to simplify the RBFNN structure and improve its anti-interference ability, RST is used to act as the pretreatment cell of RBFNN and mine useful knowledge from the diagnosis knowledge base. So a novel complex intelligent fault diagnosis (NCIRRFD) method based combining RST and RBFNN is proposed in this paper. In the proposed NCIRRFD method, RST is used to mine the rules. When their confidence and support satisfy a preset criterion, these rules are used as a diagnosis knowledge base in order to offer directly the fault diagnosis service. The proposed NCIRRFD model is shown in Figure 2.

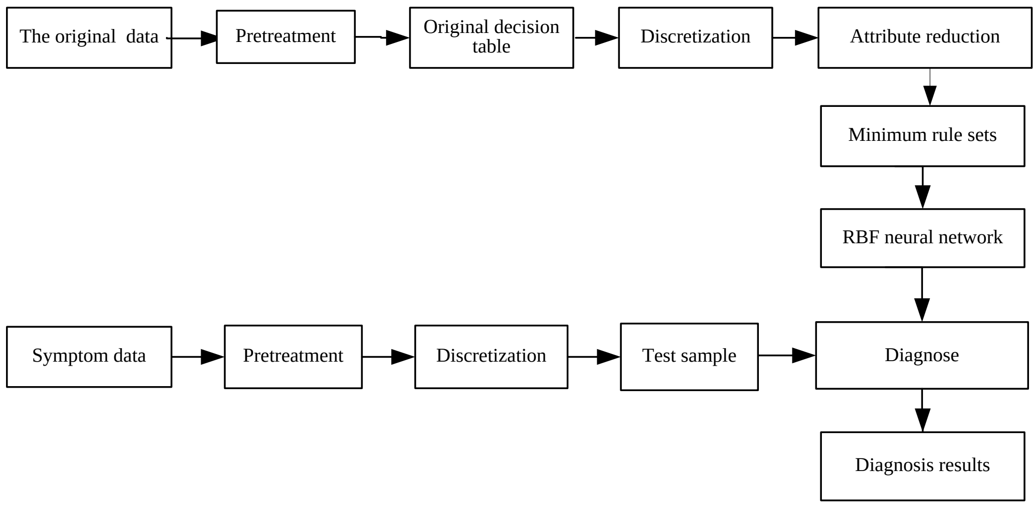

Figure 2. Structure of NCIRRFD Model Based on RST and RBFNN

From Figure 2, the steps of the NCIRRFD model are shown as follows:

Step 1. Input the original data.

Extract randomly the historical fault information from the relational database.

Step 2. Pretreatment data.

Construct relational data model in order to establish two-dimensional decision table of original fault information. Data pretreatment is carried out by some data processing in order to improve the abstract generalization of knowledge radix, reduce the physical dimension of knowledge template, and provide the involved semi-finished data set with the discovering task of mining kernel knowledge. There are some main processing methods: Data integration, data completion, data transformation and data reduction.

Step 3. Discretizate the continuous attributes.

When RST is used to process the decision table, attribute values in decision table must be discretized. Hence, in allusion to the continuous data, we must discretize these continuous data. A hybrid hierarchical k-means clustering algorithm is used to discretize the continuous data in this paper. This algorithm incorporates hierarchical clustering method with k-means clustering method to exert each excellence and overcome each disadvantage. The idea of hybrid algorithm is to carry on hierarchical clustering to obtain some initial information. Then k-means clustering method is used to refine in order to get the high quality clustering results. This hybrid algorithm is described as follows [16].

Step 4. The attribute reduction.

Since people always hope to get fewer condition attributes of reduction result, reduction is used to remove the unnecessary condition attributes and get the concise decision rule. Attribute reduction algorithm based on RST mainly includes attribute reduction on discernibility matrix and logic operation, induction attribute reduction algorithm, *etc.*. These algorithms do not adequately think over the specialty of knowledge in the data domain and flexibility. In this article, a kind of attribute significance reduction algorithm based on RST is used to reduce the decision Table [17].

Step 5. Obtain the least rule set by reduction using rough set which inputs the RBFNN model to train in order to get the RBFNN model.

Step 6. Determine the diagnosis error by the RBFNN model regarding whether to meet the requirements; otherwise, select other reduction set and return to Step 4.

Step 7. Using the NCIRRFD model to diagnose faults of the waiting fault information in order to obtain the diagnosis result.

4. The Experiment Simulation and Application

In order to validate the correctness and effectiveness of the NCIRRFD model, a centralized control system fault diagnosis case is selected in here. The fault diagnosis decision table is shown in Table 1. In Table 1, U is the universe, $x_1 \sim x_5$ is the condition attributes, they are the amplitude of frequency energy of the domain signature spectrum of the vibration signal $F < 0.3f$, $0.4 \le F \le 0.5f$, $F = 1f$, $F = 2f$ and $F \ge 4f$, f is the vibration frequency. D is the decision attribute, which indicates the different faults in the centralized control system. The $D = 1$ indicates the oil-film whipping fault, $D = 2$ indicates the imbalance fault, $D = 3$ indicates the misalignment fault.

Table 1. A Set of Fault Diagnosis Samples

U	x_1	x_2	x_3	x_4	x_5	D
c_1	0.051	0.774	0.231	0.048	0.015	1
c_2	0.235	0.978	0.309	0.059	0.020	1
c_3	0.046	0.024	0.881	0.319	0.063	2
c_4	0.011	0.055	0.383	0.185	0.254	2
c_5	0.035	0.039	0.387	0.531	0.231	3
c_6	0.012	0.035	0.427	0.495	0.176	3

First of all, these data are preprocessed in order to eliminate the questionable data and noise. The hybrid hierarchical k-means clustering algorithm is used to discretize continuous attributes. The discrete result of fault diagnosis is presented in Table 2.

Table 2. A Set of Discretization Fault Diagnosis Samples

U	x_1	x_2	x_3	x_4	x_5	D
c_1	1	2	1	1	1	1
c_2	2	2	2	1	1	1
c_3	1	1	3	2	1	2
c_4	1	1	3	1	3	2
c_5	1	1	2	2	3	3
c_6	1	1	3	3	2	3

According to the basic concept of RST, knowledge reduction for the discrete decision table is calculated in order to obtain the computation results which have analyzed the computed results. Attribute set $\{x_1, x_3, x_4, x_5\}$ is important to the original decision table in Table 3. The $\{x_1, x_3, x_4, x_5\}$ is proved to be the minimal reduction attribute set of the decision table and keeps the classification ability of the five attributes. So $\{x_1, x_3, x_4, x_5\}$ is the essential attribute for the decision system.

Table 3. A Set of Reduction Fault Diagnosis Samples

U	x_1	x_3	x_4	x_5	D
c_1	1	1	1	1	1
c_2	2	2	1	1	1
c_3	1	3	2	1	2
c_4	1	3	1	3	2
c_5	1	2	2	3	3
c_6	1	3	3	2	3

Finally, the obtained the minimum rule set is regarded as the input of the NCIRRFD model in order to train the model for obtained the optimized NCIRRFD model. Then the diagnostic information {(0.021, 0.502, 0.748, 0.125, 0.028), (0.020, 0.055, 0.482, 0.077, 0.332)} are input the optimized NCIRRFD model to make the fault diagnosis. The result of fault diagnosis is obtained. The first fault data set is $D = 2$, which indicates the imbalance fault. And the second fault data set is $D = 3$, which indicates the misalignment fault. Simulation experiments indicate that the proposed NCIRRFD method is effective and accurate for fault diagnosis in the centralized control system.

5. Conclusion

In this paper, the RST and RBFNN are introduced to improve fault diagnosis precision and decrease misinformation diagnosis. A novel intelligence fault diagnosis (NCIRRFD) model and method is proposed. In this NCIRRFD method, RST is applied to run and serve knowledge base, which can delete redundant knowledge and noise and support the dynamic update in knowledge base. The RBFNN is applied to resolve the bottle neck problem in knowledge acquisition and representation abilities. At the same time, a hybrid hierarchical k-means clustering algorithm is used to discretize the continuous data. This algorithm incorporates hierarchical clustering method with k-means clustering method to exert each excellence and overcome each disadvantage. And a kind of attribute significance reduction algorithm based on RST is used to reduce the decision table. An actual application case is selected to test and verify the proposed NCIRRFD method. The application results show that the NCIRRFD method can reduce RBF neural network training time, enhance network noise immunity and improve learning quality of RBFNN. And this method can effectively eliminate false and omit alarm of fault diagnosis and improves the diagnostic accuracy and learning speed.

References

[1] J. D. Wu and C. H. Liu, "An expert system for fault diagnosis in internal combustion engines using wavelet packet transform and neural network," Expert Systems with Applications, vol. 36 no. 3, **(2009)**, pp. 4278-4286.
[2] M. Kudo and J. Sklansky, "Comparison of algorithms that select features for pattern classifiers," Pattern Recognition, vol. 33 no. 1, **(2000)**, pp. 25-41.
[3] H. L. Sun, Z. J. He and Y. Y. Zi, "Multiwavelet transform and its applications in mechanical fault diagnosis – A review," Mechanical Systems and Signal Processing, vol. 43 no. 1-2, **(2014)**, pp. 1-24.
[4] M. R. Maurya, R. Rengaswamy and V. Venkatasubramanian, "Fault diagnosis using dynamic trend analysis: A review and recent developments," Engineering Applications of Artificial Intelligence, vol. 20 no. 2, **(2007)**, pp. 133-146.
[5] J. Lunzea and F. Schiller, "An example of fault diagnosis by means of probabilistic logic reasoning," Control Engineering Practice, vol. 7 no. 2, **(1999)**, pp. 271-278.
[6] S. S. T. Bathaie, Z. N. S. Vanini and K. Khorasan, "Dynamic neural network-based fault diagnosis of gas turbine engines," Neurocomputing, vol. 125 no. 11, **(2014)**, pp. 153-165.
[7] D. Ma, Y. H. Liang, X. S. Zhao, R. C Guan and X. H. Shi, "Multi-BP expert system for fault diagnosis of power system," Engineering Applications of Artificial Intelligence, vol. 26 no. 3, **(2013)**, pp. 937-944.
[8] V. Muralidharan and V. Sugumaran, "Rough set based rule learning and fuzzy classification of wavelet features for fault diagnosis of monoblock centrifugal pump," Measurement, vol. 46 no. 9, **(2013)**, pp. 3057-3063.
[9] A. Escobet, À. Nebot and F. Mugica, "PEM fuel cell fault diagnosis via a hybrid methodology based on fuzzy and pattern recognition techniques," Engineering Applications of Artificial Intelligence, vol. 36 no. 1, **(2014)**, pp. 40-53.
[10] M. M. Mansour, M. A. A. Wahab and W. M. Soliman, "Petri nets for fault diagnosis of large power generation station," Ain Shams Engineering Journal, vol. 4 no. 4, **(2013)**, pp. 831-842.
[11] H. Luo, Y. R. W. H. Lin and Y. Y. Jiang, "Module level fault diagnosis for analog circuits based on system identification and genetic algorithm," Measurement, vol. 45 no. 4, **(2012)**, pp. 769-777.
[12] Q. Wu, "Car assembly line fault diagnosis based on robust wavelet SVC and PSO," Expert Systems with Applications, vol. 37 no. 7, **(2010)**, pp. 5423-5429.
[13] F. F. Diego, M. R. David, F. R. Oscar and A. B. Amparo, "Automatic bearing fault diagnosis based on one-class v-SVM," Computers & Industrial Engineering, vol. 64 no. 1, **(2013)**, pp. 357-365.
[14] V. Malathi and N. S. Marimuthu, "Intelligent fault diagnosis of electrical power transmission network using FPGA," Engineering Intelligent Systems, vol. 15 no. 1, **(2007)**, pp. 241-244.
[15] Pawlak Z, "Rough sets," International Journal of Computer and Information Science, vol. 11 no. 1, **(1982)**, pp. 341-356.
[16] W. Jin and H. P. Chen, "A Hybrid Hierarchical k-means Clustering Algorithm," Journal of Hohai University Changzhou, vol. 21 no. 3, **(2007)**, pp. 7-10.
[17] X. F. Wang and W. B. Xu, "A New Method for Attributes Reduction," Microelectronics & Computer, vol. 24 no. 4, **(2007)**, pp. 99-101.

Author

Jing-Hua Zhu, Lecturer, received the Engineering Master degree in computer software from University of Electronic Science and Technology of China in 2011, Chengdu, China. The main research directions: Artificial intelligence, CAD&CG.