Fault Diagnosis for Wireless Sensor Network's Node Based on Hamming Neural Network and Rough Set

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***Abstract*—To accurately diagnose node fault in wireless sensor network (WSN) can improve long-distance service of nodes in WSN, assure reliability of information transfer and prolong lifetime of WSN. In this paper, a novel method of fault diagnosis for node of WSN was brought forward. First, attribute reduction for decision-making of fault diagnosis could be founded based discernibility matrix in rough set theory. Furthermore, a set of model for node's fault diagnosis in WSN could be built through classification algorithm based on attribute matching. Finally, a set of method for fault classification was founded by hamming network. The result of simulation shows that characteristics of this method are as follows: high veracity of diagnosis, a little expenditure of communication, low energy consumption and strong robustness.**

***Keywords*—Wireless sensor network; Rough set theory; discernibility matrix; attribute reduction; Hamming network**

I. INTRODUCTION

It is a global research hot spot of new technique to adopt automatic configuring wireless sensor network in recent years. It has very high application value in many fields. It is a key technique to prolong lifetime of WSN to the best of our abilities. The wireless sensor's structure is more and more complicated, its function is better and better and its automatic degree is higher and higher. The node in WSN will produce many faults because applied environment in WSN extreme complicated and badly. Thus it will reduce or disable scheduled function in WSN, even it will result huge loss or paralysis of entire networks. Fault diagnosis can immediately and accurately present abnormal states or fault states, avoid of faults or eliminate faults, guide operation of sensor and improve reliability, security and validity. So this can decrease fault loss to minimum limit. And this assures that WSN can implement maximum design capability because this can adequately fulfill potential of WSN and prolong its lifetime. The literature datum presently referred show as follow: On the one hand, the literature datum related to fault diagnosis in WSN is few. Secondly and it isn't found to research fault diagnosis of nodes in WSN by Rough set theory. On the other hand, the technique of WSN has greatly exceeded the technique of fault diagnosis of nodes in WSN, so fault diagnosis of nodes in WSN is especially necessary. Crash faults identification in WSN is studied in literature [1]. In this paper, based on Rough set theory, a novel method of fault diagnosis for node in WSN was brought forward. First, decision-making table of fault diagnosis could be reduced based on improved discernibility matrix algorithm resulted from attribute reduction technique in rough set theory. Furthermore, an algorithm of fault classification could be built based on Hamming neural network. Finally, simulative experiment was carried through. The result of simulation was satisfying through repeated simulative experiments.

II. BASIC STRUCTURES OF NODE IN WSN

In general, a representative systematic structure in WSN is comprised of distributed sensors, sink node, internet (A satellite may be included.) and node of task management (Figure 1). Where, sensor node in WSN forms from four modules as follows (Figure 2): sensor module (including analog signals-digital signals module), processor module (including CPU, memorizer and embedded operating system et al.), wireless communication module and power supply module.

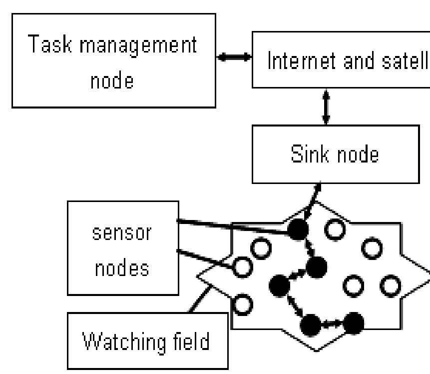

Figure 1. Systematical structures of WSN (solid circularities denote sensors of pass-path chose)

III. TECHNIQUE OF FAULT DIAGNOSIS IN WSN

Fault diagnosis is implemented in system grade, and faults according to structure of sensor node can be divided into four kinds as follows: fault in power supply module, fault in sensor module, fault in processor module and fault in wireless communication module. When different modules occur to faults, symptoms of faults are different and their attribute

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values aren't all the same. To diagnose different module, different diagnosis strategy need be adopted.

A. Fault diagnosis of each module in node

1） Diagnosis of sensor module

The rule of if…then can be adopted to diagnose fault. Let measure data be ζ, threshold value be ε, average value be θ and threshold value of outlier data be δ.

The algorithm of diagnosis in detail is as follows:
If $|\zeta-\theta|>\delta$, then sensor probe or A/D happens fault.
If $\zeta>\varepsilon$, then sensor probe or A/D happens fault.
If $\zeta=0$， then sensor probe or A/D happens fault.

2） Diagnosis of processor module

Diagnosis of processor module may be divided in detail into three parts as follows:

a) Diagnosis of instructions system

Run the procedure. If executing result is different destine result, then instructions system has faults; or else instructions system can't be assured of faults. The procedure including enough instructions should be designed to test instructions system.

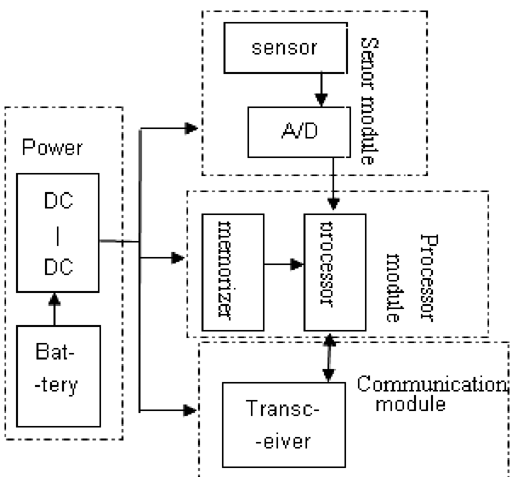

Figure 2. Structures of node in WSN

b) RAM diagnosis in chip

First, the content in RAM is read and save duplicate. Secondly, reverse of the content in binary is gotten and written in original address. Finally, the content in original address is read and compare with original content in detail. If the content read is the same as original content, then it is considered that RAM has no faults.

c) Timer diagnosis

The interrupting procedure is designed. If procedure can overflow on time and clear overflowing symbol bit, then timer has no faults, or else timer has faults.

3） Diagnosis of wireless communication module

If node can reply on every inquiring command, the communication module is considered to be normal. If node can't reply on inquiring commands and can send out information on schedule, the communication module is considered to have faults. If the communication module can exactly pass data of other node, the communication module is considered to be normal, or else it is considered to have faults.

4） Diagnosis of power supply module

If node can't reply on inquiring commands and can't send out information on schedule, the power supply module is considered to have faults.

B. Building of Fault diagnosis attribute table in WSN

TABLE I. FAULT SYMPTOMS OF NODE IN WSN INCLUDING THEIR ATTRIBUTIONS

number	symptoms types	attribute value
m[1]	Can node answer when sending out inquiring command?	m[1]=0 (yes) m[1]=1 (no)
m[2]	Can node return signals on schedule?	m[2]=0 (yes) m[2]=1 (no)
m[3]	Can node exactly execute instructions?	m[3]=0 (yes) m[3]=1 (no)
m[4]	Are measure data always zero?	m[4]=0 (no) m[4]=1 (yes)
m[5]	Is measure-datum far from average value?	m[5]=0 (no) m[5]=1 (yes)
m[6]	Can node transfer other node's datum?	m[6]=0 (yes) m[6]=1 (no)
m[7]	Is measure-datum far bigger than normal value?	m[7]=0 (no) m[7]=1 (yes)
m[8]	Absolute value of difference between adjacent sensor's measure data.	m[8]=0 (<0.5) m[8]=1 （≥0.5）

TABLE II. FAULT TYPES OF NODE IN WSN INCLUDING THEIR SYMPTOMS

number	fault types	symptoms
d1	normal	Every module is normal.
d2	fault of power supply module	m[1],m[2],m[3],m[4],m[5], m[6],m[7],m[8]
d3	fault of sensor's module	m[4],m[5], m[7],m[8]
d4	fault of CPU module	m[1],m[2],m[3], m[6]
d5	fault of wireless communication module	m[1],m[2],m[6]

For briefness and no losing universality, the paper only diagnoses typical four faults as follows: fault in power supply module, fault in sensor module, fault in processor module and fault in wireless communication module. The table of fault symptoms of node in WSN including their attributions(table Ⅰ) and the table of fault types of node in WSN including their symptoms(table Ⅱ) are respectively built to rapidly diagnose fault of node in WSN through analyzing structure and fault types of WSN.

IV. REDUCTION OF INFORMATION ON FAULT DIAGNOSIS

Rough set theory has an ability using incomplete information or knowledge to process fuzzy phenomena and classifying datum according to observing or measuring some imprecise result [2], [3], [4]. Because of fault diversity of node in WSN and bad application condition, information obtained is very inadequate and uncertain. Thus, accurate diagnosis of fault of node in WSN is extreme difficult. Fortunately, rough set theory is with facility in deal with the problem with incomplete information and it can easily resolve fault diagnosis online with low energy consuming by datum reduction theory of rough set.

The datum reduction is a key technique of rough set theory. The datum reduction is to omit redundancy, unrelated and unimportant datum in preserving classified ability of datum so as to make datum classification simple and clear. In this paper, the datum reduction is to process attribute reduction of decision-making table and make a record in decision-making table denote sample with same characteristic. In this way, the decision-making rule holds high adjustability. In this paper, fault diagnosis is implemented by attribute reduction algorithm based on improved discernibility matrix and Boolean calculation.

According to rough set theory, the reduction method for fault diagnosis information of node in WSN is as follow.

Let P be a group of equivalent relations and $R \in P$. If

$$ind(P) = ind(P - \{R\}) \quad (1)$$

Then R is unnecessary in P ; or else R is necessary. If every R is necessary, then P is independent; or else P is dependent. If two objects have the same information, viz. they can't be differentiated, and then they are considered as a equivalent relation. The $ind(P)$ is called as intersection of all equivalent relations of P .

Let U be a universe and P be a group of equivalent relations defined in U . Then the set composed of all absolute necessary relations in P is called absolute core of P , viz. $CORE(P)$ .If $ind(Q) = ind(P)$ and Q is independent, then Q is called as an absolute reduction of P . The absolute core doesn't equal to reduction, it subordinates to reduction and it equals to intersection of all reductions.

Let decision-making system be $S =< U, R, V, f >$. Where, $R = P \cup D$ is attributes set, $P = \{m[i] | i = 1,..., k\}$ and $D = \{d\}$ are respectively called as condition attribute set and decision-making set, $U = \{x_1, x_2,..., x_n\}$ is a universe and $m[i](x_j)$ is value of sample x_j in $m[i]$. $C_D(i, j)$ denotes a nodical element of i th row and j th column in that it is point of intersection in discernibility matrix C_D . So C_D is defined as follow:

$$C_D(i, j) = \begin{cases} m[k], d(x_j) \neq d(x_i) \\ 0, d(x_j) = d(x_i) \end{cases} \quad (2)$$

Where, $\{m[k] | m[k] \in P \wedge m[k](x_i) \neq m[k](x_j)\}$.

The discernibility matrix is a symmetrical matrix, therefore this paper only needs consider upper trigonal part or lower trigonal part. The discernibility matrix defined shows that $C_D(i, j)$ is a set of all attributes differentiated between x_i and x_j . The core and reduction of P can be easily resolved by discernibility matrix. Where, the core may be defined as a set of items only included an element in discernibility matrix, viz.

$$CORE(P) = \{ m \in P : C_D(i, j) = (m) \text{ for some } i, j \} \quad (3)$$

If the attribute set $B \subseteq P$ is a least attribute subset and accord with the condition as follow

$$B \cap C_D(i, j) \neq \phi , \text{当} C_D(i, j) \neq \phi \quad (4)$$

Then call the attribute set $B \subseteq P$ is a reduction of P . At a word, a reduction is a least attribute subset that it can distinguish all objects divided by the whole attribute set P . The algorithm of finding B accorded with the condition is as follow:

1) Working-out discernibility matrix $C_D(i, j)$;

2) Reduce discernibility matrix $C_D(i, j)$, extract the single attribute element set as core attribute in $C_D(i, j)$ and let its value as 0;

3) When $C_D(i, j) \neq 0$ and $C_D(i, j) \neq \phi$, the disjunctive logic expression T_{ij} can be built as follow:

$$T_{ij} = \vee_{m[i] \in C_D(i,j)} m[i] \quad (5)$$

4) Let all T_{ij} process conjugative operation and get a conjugative normal form T as follows:

$$T = \wedge_{C_D(i,j) \neq 0 \; C_D(i,j) \neq \phi} T_{ij} \quad (6)$$

5) Finally, the disjunctive normal form T' can be found through conversion of T as follow:

$$T' = \vee_i T_i \quad (7)$$

6) Let core attribute join in every conjugative item, then each conjugative item in T' is corresponding to a result of attribute reduction.

The algorithm shows that the discernibility matrix is provided with interpretative function and is relatively intuitionistic. Its essential is datum reduction by absorption in logic operation and other deductive principle.

V. FAULT CLASSIFICATION BASED ON HAMMING NETWORK

The paper brings forward fault classification algorithm based on Hamming network [5] by the samples after attribute reduction mentioned above. Suppose p normal samples of n dimensionality as follows: c^1 , c^2 , … , c^p ; What is classification of vector x ? Hamming network is as figure 3. The algorithm is as follows:

1) Let link weight of feedforward layer $w_{i,j} = c_i^j / 2$ $(j = 1,2,..., p; i = 1,2,..., n)$, c_i^j denotes i th element of vector c^j of j th samples. The threshold of feedforward layer is defined as $\theta_j = -n / 2$ $(j = 1,2,..., p)$. Let sigmoid function of feedforward layer be $f1(x) = x / n$ and $t = 0$.

2) Through feedward layer, then can get formula as follows:

$$r_j(t) = (\sum_{i=1}^{n} w_{i,j} x_i - \theta_j) / n \text{ (j=1,2,…, } p \text{).}$$

3) Let the threshold of competition layer be 0 and sigmoid function is as follows.

$$f(k)=\begin{cases}0, & k<0\\ k, & k\geq 0\end{cases}.$$

4) Arbitrarily select e *satisfied with* $0<e<1/(p-1)$

5) $r_j(t+1)=f(r_j(t)-e\sum_{m\neq j} r_m(t))$ *(j=1,2,..., p).*

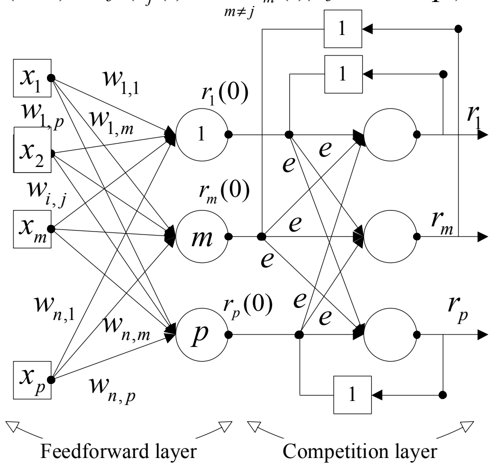

Figure 3. Hamming network

6) $\delta=\sum_{j=1}^{p}(r_j(t)-r_j(t+1))$.

7) If $\delta\neq 0$, then $t=t+1$. Go to 5).

8) If $r_j(t+1)$ is positive, then it is corresponding classification of vector x .

9) End.

The essential of the algorithm is parallel calculation that n subtracts every Hamming distance. Hamming network can adjust the algorithm to fault mode classification implement possessed minimum error and give a fault mode to match unbeknown input fault mode.

VI. THE SIMULATIVE EXPERIMENT AND RESULT ANALYSIS

The table of fault sample decision-making of nodes in WSN (table Ⅲ) can be built through the table of fault symptoms of node in WSN including their attributions (table Ⅰ) and the table of fault types of node in WSN including their symptoms (table Ⅱ). The discernibility matrix $C_D(i,j)$ (Formula 8) can be built by table Ⅲ.

Where, the U denotes sample object, the m denotes attribute type, the D denotes decision-making type.

TABLE III. FAULT SAMPLE DECISION-MAKING OF NODES IN WSN

U / m	1	2	3	4	5	6	7
m[1]	0	1	0	0	0	1	0
m[2]	0	1	0	0	0	0	0
m[3]	0	1	0	1	0	0	0
m[4]	0	1	1	0	0	0	0
m[5]	0	1	1	0	1	0	0
m[6]	0	1	0	0	0	1	0
m[7]	0	1	0	0	1	0	0
m[8]	0	1	1	0	1	0	1
D	d1	d2	d3	d4	d3	d5	d3

$$\begin{pmatrix} 0 & a_{1,2} & a_{1,3} & m[3] & a_{1,5} & m[1]m[6] & m[8]\\ & 0 & a_{2,3} & a_{2,4} & a_{2,5} & a_{2,6} & a_{2,7}\\ & & 0 & a_{3,4} & 0 & a_{3,5} & 0\\ & & & 0 & a_{4,5} & a_{4,6} & m[3]m[8]\\ & & & & 0 & a_{5,6} & 0\\ & & & & & 0 & a_{6,7}\\ & & & & & & 0 \end{pmatrix} \quad (8)$$

where, $a_{1,2}$ = m[1]m[2]m[3]m[4]m[5]m[6]m[7]m[8],
$a_{1,3}$= m[4]m[5] m[8], $a_{1,5}$= m[5]m[7]m[8],
$a_{2,3}$= m[1]m[2]m[3]m[6]m[7],,
$a_{2,4}$= m[1]m[2] m[4]m[5]m[6]m[7]m[8],
$a_{2,5}$= m[1]m[2]m[3]m[4] m[6],
$a_{2,6}$= m[2]m[3]m[4]m[5] m[7]m[8],
$a_{2,7}$ = m[1]m[2]m[3]m[4]m[5]m[6]m[7],
$a_{3,4}$= m[3]m[4]m[5] m[8],
$a_{3,5}$= m[1] m[4]m[5]m[6] m[8],
$a_{4,5}$= m[3]m[5] m[7]m[8], $a_{4,6}$= m[1]m[3]m[6],
$a_{5,6}$= m[1] m[5]m[6]m[7]m[8], $a_{6,7}$= m[1]m[6]m[8]。

After datum reduction algorithm be called, the conjugative item can be gotten by the discernibility matrix $C_D(i,j)$ as follow.

$$T' = m[1]\wedge m[3]\wedge m[6]\wedge m[8].$$

So, a reduction {m [1], m[3], m[6], m[8]} can be found and table 3 can be reduced as table Ⅳ.

TABLE IV. THE TABLE OF FAULT SAMPLE DECISION-MAKING OF NODES IN WSN AFTER REDUCTION

m / U	m[1]	m[3]	m[6]	m[8]	D
1	0	0	0	0	d1
2	1	1	1	1	d2
3	0	0	0	1	d3
4	0	1	0	0	d4
5	1	0	1	0	d5

TABLE V. RESULT ON FAULT DIAGNOSIS

Algorithm applied in simulation	**Preciseness rate of fault diagnosis**
Algorithm brought forward in the paper	98.2%
Algorithm of traditional decision-making table	96.1%

Finally, the simulative experiment of fault classification is implemented based on Hamming network mentioned above fourth section in Matlab. The WSN is prone to produce datum difference for complicated application environment and noise disturbance. Suppose that reliability of each data applied to fault classification reaches 99.5% and 200 group data are implemented to classify. Compared to traditional decision-making table only applied to, their statistical results are as follows (table Ⅴ).

If reliability of each data applied to fault classification drops at 98.5% and 200 group datum are implemented to classify. Finally, the table of fault diagnosis result (table VI) can be found as follow:

TABLE VI. RESULT ON FAULT DIAGNOSIS

Algorithm applied in simulation	Preciseness rate of fault diagnosis
Algorithm brought forward in the paper	94.5%
Algorithm of traditional decision-making table	89.9%

The simulative experiment shows that preciseness rate of fault diagnosis adopted the algorithm of the paper is higher 2.1% than the preciseness rate adopted to the algorithm of traditional decision-making table if reliability of each data applied to fault classification reaches 99.5%. If reliability of each data applied to fault classification drops at 98.5%, the preciseness rate of fault diagnosis adopted to the algorithm of the paper is higher 4.6% than the preciseness rate adopted to the algorithm of traditional decision-making table Actually, the process of fault diagnosis is a process of searching for attribute matching and the reliability of the datum regarded as divisional warrant can not insure 100% preciseness. It easily happens to misdiagnose or be incapable of diagnosis to apply traditional decision-making table to diagnose because it needs that many attributes diagnosed and it is heavily influenced by false datum. Thus, the algorithm brought forward in the paper enormously reduces the effect. The attribute reduction of datum hugely reduces objects searched for and avoids of disadvantage effect of redundant attributes on diagnosis preciseness. Especially, more misdiagnosis will happen and more attributes need to be diagnosed because the reliability of datum of nodes in WSN is very low. Furthermore, the parallel algorithm of Hamming network improves validity of search. So the algorithm can rapidly and accurately accomplish task of fault diagnosis of nodes in WSN.

VII. CONCLUSIONS

The algorithm of fault classification based on Rough set theory can rapidly and accurately accomplished task of fault diagnosis of nodes in WSN. When reliability of datum drops, the advantage in diagnosis preciseness rate and diagnosis velocity is more obvious. Even though some redundant attributes can't attain or some information is false, fault of nodes in WSN also can be accurately diagnosed. Thus, it can improve on robustness of fault diagnosis and resolve technique problem of fault diagnosis of nodes in WSN with limited energy and notable indetermination. The experimental result shows validity of the method.

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