Applied Mathematics and Nonlinear Sciences

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The Comprehensive Diagnostic Method Combining Rough Sets and Evidence Theory

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Submission Info

Communicated by Juan Luis García Guirao

Received January 14th 2021

Accepted February 26th 2021

Available online May 25th 2021

Abstract

To solve the difficulties in practice caused by the subjectivity, relativity and evidence combination focus element explosion during the process of solving the uncertain problems of fault diagnosis with evidence theory, this paper proposes a fault diagnosis inference strategy by integrating rough sets with evidence theory along with the theories of information fusion and meta-synthesis. By using rough sets, redundancy of characteristic data is removed and the unrelated essential characteristics are extracted, the objective way of basic probability assignment is proposed, and an evidence synthetic method is put forward to solve high conflict evidence. The method put forward in this paper can improve the accuracy rate of fault diagnosis with the redundant and complementary information of various faults by synthesizing all evidences with the rule of the composition of evidence theory. Besides, this paper proves the feasibility and validity of experiments and the efficiency in improving fault diagnosis.

Keywords: fault diagnosis; information fusion; rough sets; D-S evidence theory

1 Introduction

Information fusion is applied widely during fault diagnosis and there are many ways. Evidence theory or D-S theory (DST) [1, 2] can compound the uncertain information from several information sources and is a very effective uncertainty reasoning way in information fusion technology. However, the evidence theory itself has some problems [3], such as dependency on the evidence provided by expert knowledge, focus element

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explosion caused by evidence combination, rigorous demands to combination conditions (mutual independence among evidences), inefficiency to evidential conflicts and the subjectivity in the distribution of credibility and so on. Many scholars have improved the theory to overcome these limitations, but still there are some deficiencies [4–6]. Rough set theory is a new mathematical tool to deal with vagueness and uncertain knowledge and is very practical. It can extract unrelated essential characteristics to eliminate redundancies without any initial or additional data [7, 8]. Both the rough set and evidence theories are math tools for uncertain information and they focus on the group ability. There is a strong complementary relationship between these two theories [9–11]. This paper provides a new research thought for intelligent fault diagnosis by combining the evidence theory with rough set theory to solve the subjectivity, relativity, integrated focus element explosion and conflict problems of evidences, improve the accuracy of fault diagnosis and at last carry out online diagnostics.

2 Basic Theories

2.1 Rough Set Theory

The paper just gives two definitions about the importance of attribute and the basic ideas about rough set theory, which are referred in the literature [12].

Definition 1. The importance of any attribute $a \in (C - R)$ about D is defined as:
 $SGF(a, R, D) = \gamma(R \cup \{a\}, D) - \gamma(R, D)$

Definition 2. To $B \subseteq C$, if B is independent to D , and also $\gamma(C, D) = \gamma(B, D)$, then B is a D relative reduction of C .

2.2 D-S Evidence Theory

Here the paper just gives the D-S evidence theory synthesis formula and the related knowledge, which are referred in the literature [1, 2].

Definition 3. If $Bel_1, Bel_2, \dots, Bel_n$ is the belief function on the same identification framework and Θ and $m_1, m_2, \dots, m_n$ are the basic probability assignments that correspond to them, then the basic probability assignment after synthesis is:

$$m(A) = \begin{cases} 0 & A = \varnothing \\ \frac{\sum_{\cap A_n=A} \prod_{n=1}^N m_n(A_n)}{\sum_{\cap A_n \neq \varnothing} \prod_{n=1}^N m_n(A_n)} & \forall A \neq \varnothing \end{cases} \quad (1)$$

Among them: $k = \sum_{\cap A_n=\varnothing} \prod_{n=1}^N m_n(A_n) \forall A \subset \Theta$ reflects the degree of conflict of evidences. Definition 3 is the combination rule of D-S theory (DST).

2.3 Improvement of D-S Evidence Synthesis Rule

From the D-S evidence theory synthesis formula: when $k = 1$, it shows that evidences conflict completely and fusion cannot be done; when $0 < k < 1$, synthesis formulas can be applied, while $k \rightarrow 1$ and evidences conflict highly, the synthesis formula will lead the perverse conclusion. Many scholars have made some significant achievements about evidence conflict probability distribution function; Sun Quan proposed a new synthesis formula by analyzing the advantages and disadvantages of evidence synthesis rules of DST, and Yager performed the synthesis of conflicts in a better way at different degrees. The synthesis formula is as follows [13]:

$$m(\varphi) = 0 ; m(A) = \sum_{\cap A_n = A} \prod_{n=1}^N m_n(A_n) + f(A) \quad \forall A \neq \varphi ; m(\Theta) = \sum_{\cap A_n = \Theta} \prod_{n=1}^N m_n(A_n) + f(\Theta)$$

$$f(A) = k\varepsilon q(A)(q(A) = \frac{1}{n} \sum_{1 \leq i \leq n} m_i(A)) \quad (2)$$

$$f(\Theta) = k\varepsilon q(\Theta) + k(1 - \varepsilon) \quad (3)$$

Among them: n is the number of evidences; the reliability of evidence ε is

$$\varepsilon = e^{-\tilde{k}} (\tilde{k} = \frac{1}{n(n-1)/2} \sum_{i < j} k_{ij} \quad i, j \leq n, k_{ij} = \sum_{A_i \cap A_j = \Omega} m_i(A_i) m_j(A_j)) \quad (4)$$

Eq. (4) has some subjective factors, while the physical meaning of Eqs (2) and (3) is not clear. Since $q(A)$ is the average supporting degree of evidence to A , evidence conflict probability k can be assigned in proportion to A . That is weighing and assigning the probability of evidential conflict according to the supporting degree of each proposition; also because of the differences of importance degree of each evidence source, the evidence weight factor is introduced. In this paper, a new evidence synthesis way is proposed:

$$m(\varphi) = 0 ; m(A) = \sum_{\cap A_n = A} \prod_{n=1}^N m_n(A_n) + kq'(A) \quad \forall A \neq \varphi ; q'(A) = \sum_{1 \leq i \leq n} w_i m_i(A)$$

Among them: $k = \sum_{\cap A_n = \varphi} \prod_{n=1}^N m_n(A_n) \forall A \subset \Theta$; w_i is the weight of $No.i$ evidence source, and this paper gives the self-conflict of evidence to determine the evidence weight coefficient.

Definition 4. Suppose the conflict sum of evidence i and evidence j ($j = 1, 2, \dots, i-1, i+1, \dots, n$) is the amount of self-conflict ϕ_i of evidence i , the expression is $\phi_i = \sum_{j=1, j \neq i}^n \sum_{A_i \cap A_j = \varphi} m_i(A_i) m_j(A_j)$ (n is the number of evidence),

then: $w_i = \frac{1}{\phi_i} / \sum_{j=1}^n \frac{1}{\phi_j} \quad i = 1, 2, \dots, n$.

Definition 4 shows the greater the amount of self-conflict for evidence, the smaller its weight factor is. Otherwise, the smaller the amount of self-conflict for evidence, the greater its weight factor is. The weight factor shows the important degree of evidences provided by the information source in the synthesis process and the incidence of the synthetic results.

Here is an example to prove the validity of the way. Suppose $\Theta = \{A, B, C\}$, three evidences are as follows:

$m_1 : m_1(A) = 0.98, m_1(B) = 0.01, m_1(C) = 0.01$;

$m_2 : m_2(A) = 0, m_2(B) = 0.01, m_2(C) = 0.99$;

$m_3 : m_3(A) = 0.9, m_3(B) = 0, m_3(C) = 0.1$.

Three evidences are synthesised by applying the synthetic methods of DST, Yager [14], Sun Quan, Li Bicheng [15] and the synthesis method proposed in this paper, respectively (evidence weight $w_1 = 0.37414$, $w_2 = 0.21902$, $w_3 = 0.40684$) and the results are shown in Table 1. Table 1 shows the evidence synthetic method with the weight factor raised in this paper that can enhance the reasonability and reliability in the evidence combination. It can avoid the subjectivity and randomness from the weight factor by determining the evidence weight coefficient with the amount of evidence self-conflict, reflect the importance of evidence during synthesis and get a better result than other methods.

Application of the attribute reduction of the rough set can effectively optimise the key features as the evidence for diagnosis decisions. Attributes significance of rough set can evaluate the weight of each evidence objectively. And then there comes the formula $w_i = SGF(i, R, D) / \sum_{j \in C} SGF(j, R, D)$.

Table 1 Comparison of results of various evidence synthesis methods.

Synthesis formula	k	$m(A)$	$m(B)$	$m(C)$	$m(\Theta)$
DST	0.99901	0	0	1	0
Yager	0.99901	0	0	0.00099	0.99901
Sun Quan	0.99901	0.3210	0.0030	0.1880	0.4880
Li Bicheng	0.99901	0.6260	0.0067	0.3673	0
This paper	0.99901	0.7321	0.0059	0.2620	0

3 Inference method of rough set and evidence theories

This paper creates a fault diagnosis model based on inference strategy to fuse rough set and evidence theories, as shown in Figure 1. First, the basic thought is building an information decision table by discretising the fault sample data sets with continuous attributes. Then, optimising feature parameters suitable for fault diagnosis as theory body by applying the rough set theory for attribute reduction of the decision table. In practice, for the discretised sample set to diagnose, basic probability assignment of related evidences can be calculated based on the reduction and the diagnosis result can be obtained with the inductive decision by the use of the D-S combination rule.

Fig. 1 Structure of diagnostic model integrated with evidence theory and rough set.

3.1 Discretisation of continuous data sample

A rough set theory can deal with discretised data, while original sample data are always continuous, so continuous data should be discretised first. There are many ways to discretise and each has its advantage. In practice, each field seeks a proper algorithm according to the characteristic [16, 17].

3.2 Symptom attribute reduction

Symptom attribute reduction can reduce the relativity among evidence and decide the fault with attributes as less as possible, remaining the sorting quality invariant and avoiding focus element explosion. On the other hand, the weight of each attribute can be obtained from the information in the decision table and the subjectivity from experts can be avoided, overcoming the difficulties in practical application efficiently caused by the subjectivity and relativity of evidence during the fault diagnosis with evidence theory. About the reduction algorithm of the rough set theory, still there is no recognised and high-efficient algorithm. With the completion of the reduction algorithm considered, attribute reduction is applied in this paper by combining discernibility matrix, dependability of attribute and the heuristic reduction algorithm of information entropy by improving the importance of attribute. The detailed process of this algorithm is referred in the literature [18, 19].

3.3 Basic probability assignment of evidence

Basic probability assignment of evidence is realised with the decision attribute D in the decision table as the recognition framework Θ of evidence theory and with all the condition attribute $r(r \in R)$ after reduction in the decision table as the corresponding evidence. Many scholars have researched the relation between the reliability calculations of evidence theory and rough set theory [10, 11]. Since initial or additional data are not necessary for rough set theory, the basic probability assignment on rough set theory is more objective.

Theorem 1. *If $X \subseteq U$, equivalence relation $U/R = X_1, X_2, \dots, X_n$, then the measure of lower approximation of X $q(X) = |apr(X)|/|U|, X \subseteq U$ ($apr(\cdot)$ is the lower approximation) is a belief function, the basic probability assignment is: $m(x_i) = |X_i|/|U|, i = 1, 2, \dots, n; m(A) = 0, A \notin U/R$.*

Theorem 2. *If Bel is a belief function meeting the needs of the following condition: the focus element of Bel is equivalence class of U ; the basic probability assignment of the focus element of Bel A is: $m(A) = |A|/|U|$, then there exists a Pawlak rough algebra meeting with $q(X) = Bel(X), X \subseteq U$.*

The proof of Theorems 1 and 2 can be referred in the literature [10]. From Theorems 1 and 2, it is possible to calculate belief function based on a decision table with rough set theory. It provides the theoretical basis for the fusion reasoning of evidence theory and rough set theory.

The basic probability assignment $m(A) = \sum_{B \subseteq A} (-1)^{|A-B|} Bel(B)$ can be calculated by defining the belief function $Bel(A) = \sum_{B \subseteq A} m(B) \quad (\forall A \subset \Theta)$. From Theorem 1, the belief function is equivalent with a lower approximation. Considering the inconvenience of this expression in practical application, this paper provides a simple algorithm with the potential of set:

$$m(A) = \begin{cases} |A|/|U| & (A \in U/P) \\ 0 & (A \notin U/P) \end{cases} \quad (5)$$

Here P is indiscernibility relation. It is clear that Eq. (5) meets with Theorems 1 and 2.

Next, a practical algorithm of basic probability assignment is given based on a rough set decision table:

{Input: decision table after reduction; samples to be diagnosed}; {Output: basic probability assignments of all evidences}.

- 1) Quantification of samples to be diagnosed: to discretise the samples to be diagnosed according to the discretisation criterion of original sample data;
- 2) Recognition framework Θ is decision attribute set and the reasoning evidence is condition attributes $r(r \in R)$;
- 3) To determine the division U/Θ of Θ to U ;
- 4) To determine the division U/R of R to U with evidence r_i as equivalence relation R ;
- 5) To determine equivalence class in U/R and to determine each intersection of the equivalence and U/Θ according to the discrete value of the samples to be diagnosed in evidence r_i ;

6) To get the basic probability assignment of evidence r_i to from Eq. (5).

3.4 The discount of evidence and reasoning decision

If there is only $1 - \alpha$ ($\alpha \in [0, 1]$) confidence to the whole evidence, is considered as the discount rate. Considering discount to evidence, the calculation of basic probability assignment is as follows:

$$m^\alpha(A) = (1 - \alpha)m(A) \quad \forall A \subset \Theta \quad A \neq \emptyset; \quad m^\alpha(\Theta) = (1 - \alpha)m(\Theta) + \alpha$$

The diagnosis can be concluded based on the decision of basic probability assignment after a combination of the D-S rule [20].

4 Diagnosis examples

The engine is an important equipment of a ship, concerning the survivability and battle effectiveness of a ship. The performance of the engine can influence and restrict the performance of the technique and tactics of a ship. The structure of the engine is complex, while the fault analysis to it is difficult. To ensure the accuracy of fault diagnosis, more characteristic parameters should be used. The number of characteristics to be extracted gets larger with the increase of various kinds of parameters and this makes the amount of information to be processed too large and cannot meet the needs of online diagnosis. Only a few key characteristics are sensitive to a fault. They are independent and provide complementary information for each other to improve the accuracy of diagnosis. While the redundant characteristics are not sensible to fault or they are related to other characteristics but useless. The rough set theory can eliminate redundant information effectively, select the key characteristics, get probability assignment and make reasoning decisions with D-S combination rule to solve the problems such as subjectivity in evidence obtaining, relativity of evidence and focus element explosion of evidence combination.

4.1 The extraction of evidence information

After the experiments of five fault phenomena appearing in a kind of ship engine and the management to the diagnostic knowledge, this paper selects 10 sets of data samples to build. The common fault information is shown in Figure 2. In Figure 2, U stands for n ($n=10$) states of the engine, $C=\{\text{cooling water temperature } C_1, \text{ airflow } C_2, \text{ fuel pressure } C_3, \text{ revolution speed } C_4, \text{ torque } C_5\}$ stands for the five characteristic (symptom) parameters to describe the state of equipment, $D=\{\text{normal } D_1, \text{ high- temperature } D_2, \text{ airflow meter damage } D_3, \text{ fuel injector fault } D_4, \text{ ignition fault } D_5\}$ shows the fault symptoms to each state of the equipment. Select three sets of data randomly as the test samples (to be diagnosed) to verify the diagnostic effects from the method proposed in this paper.

The attribute value of the sample data in Table 2 is continuous and needs to be discretised. Here a discretisation for continuous attribute value based on SOFM network classification is used and the details and the computing process of this algorithm can be referred in the literature [21]. The decision table after discretisation is shown in Table 3. After attribute reduction with the method proposed in this paper, only three condition attributes, C_1, C_2, C_5 , are kept in the decision table. They are the diagnostic proofs for five fault symptoms: cooling water temperature (E_1), air flow (E_2), torque (E_3).

From Definition 1, the importance of attribute C_1, C_2, C_5 about D can be obtained:

$$SGF(C_1, R, D) = \gamma(R \cup \{C_1\}, D) - \gamma(R, D) = 5/7 \quad SGF(C_2, R, D) = SGF(C_3, R, D) = 2/7$$

It shows C_1 is the attribute that influences the accuracy mostly to diagnostic decision rule, followed by C_2 and C_5 . This agrees with the engineering practice. Then the weight of each evidence E_i ($i=1,2,3$) can be obtained from the following equation

$$w_i = SGF(i, R, D) / \sum_{j \in C} SGF(j, R, D) = (\omega_1, \omega_2, \omega_3) = (0.56, 0.22, 0.22).$$

Table 2 Table of fault information.

U		$m(C_1)$	$m(C_2)$	$m(C_3)$	$m(C_4)$	$m(C_5)$	D
Original samples	1	0.95	1.40	1.20	5100	0.39	D_1
	2	0.70	1.74	0.94	3450	0.98	D_1
	4	0.06	1.73	0.98	3900	0.91	D_2
	5	0.65	3.31	0.63	1950	0.55	D_3
	7	0.30	1.31	1.32	4350	0.40	D_4
	8	0.28	1.23	1.11	4300	0.44	D_4
	10	0.05	2.47	1.01	3800	0.20	D_5
Test samples	3	1.02	1.73	0.57	3500	0.98	D_1
	6	0.67	3.71	0.77	1900	0.45	D_3
	9	0.18	0.95	1.14	3600	0.30	D_5

Table 3 Decision table after discretization.

U		C_1	C_2	C_3	C_4	C_5	D
Original samples	1	3	1	3	3	2	D_1
	2	2	2	2	2	3	D_1
	4	1	2	2	2	3	D_2
	5	2	3	1	1	2	D_3
	7	2	1	3	3	2	D_4
	8	1	1	2	3	2	D_4
	10	1	2	2	2	1	D_5
Test samples	3	3	2	1	2	3	verify D_1
	6	2	3	1	1	2	verify D_3
	9	1	1	2	2	1	verify D_5

4.2 Basic probability assignment and D-S evidence theory

For evidence E_1, E_2, E_3 , the basic probability assignment can be calculated with $\alpha=0.05$ as the discount rate. In Table 3, the attribute values of test sample 6 and original sample 5 are the same after discretisation, so the diagnostic decision is the same necessarily and D_3 need not be verified anymore. For the two sets of test samples, D_1 and D_5 are fused with D-S evidence theory and the combining method by improving evidence proposed in the paper, the basic probability assignments are shown in Tables 4 and 5. Θ is the overall uncertainty.

4.3 The analysis and explanation of diagnosis

From Tables 4 and 5, the case cannot be diagnosed and a diagnostic error will occur if the diagnosis is with single evidence. For example, E_2 and E_3 in Figure 4 cannot be diagnosed, E_2 in Table 5 is a diagnostic error. The diagnostic capability of single evidence is limited. So it is necessary to combine all the evidence to get a better diagnosis. The diagnostic capability can be improved because the overall uncertainty reduces in comparison with a single evidence diagnosis after two evidences are combined. But it is possible for the case that cannot be diagnosed or diagnostic errors because of the limitation of self-capability of single evidence and original training samples, for example, $E_2 \oplus E_3$ in Table 4 cannot be diagnosed, and $E_1 \oplus E_2$ in Table 5 is a diagnostic error. For some evidences, the diagnosis is not certain after fusion, the uncertainty is reduced gradually. After the fusion of all evidences E_1, E_2, E_3 , certainty strengthens. With one evidence or two evidences, the case cannot be diagnosed or diagnostic errors may occur, while with three evidences fused the correct diagnosis can

Table 4 Basic probability assignment about D_1 .

Verify D_1		K	$m(D_1)$	$m(D_2)$	$m(D_3)$	$m(D_4)$	$m(D_5)$	$m(\Theta)$
E_1		0	0.9500	0	0	0	0	0.05
E_2		0	0.3167	0.3167	0	0	0.3167	0.05
E_3		0	0.4750	0.4750	0	0	0	0.05
$E_1 \oplus E_2$	DS	0.6017	0.9144	0.0397	0	0	0.0397	0.0062
	Improve DS		0.8269	0.0703	0	0	0.0703	0.0325
$E_1 \oplus E_3$	DS	0.4512	0.9522	0.0433	0	0	0	0.0045
	Improve DS		0.8899	0.0850	0	0	0	0.0251
$E_2 \oplus E_3$	DS	0.6017	0.4771	0.4771	0	0	0.0397	0.0062
	Improve DS		0.4282	0.4282	0	0	0.1111	0.0325
$E_1 \oplus E_2 \oplus E_3$	DS	0.7972	0.9488	0.0469	0	0	0.0039	0.0006
	Improve DS		0.7534	0.1498	0	0	0.0569	0.0399

Table 5 Basic probability assignment about D_5 .

Verify D_1		K	$m(D_1)$	$m(D_2)$	$m(D_3)$	$m(D_4)$	$m(D_5)$	$m(\Theta)$
E_1		0	0	0.3167	0	0.3167	0.3167	0.05
E_2		0	0.3167	0	0	0.6334	0	0.05
E_3		0	0	0	0	0	0.9500	0.05
$E_1 \oplus E_2$	DS	0.7020	0.0531	0.0531	0	0.8326	0.0531	0.0081
	Improve DS		0.0794	0.1746	0	0.5339	0.1746	0.0375
$E_1 \oplus E_3$	DS	0.6017	0	0.0398	0	0.0398	0.9145	0.0060
	Improve DS		0	0.1520	0	0.1520	0.6636	0.0324
$E_2 \oplus E_3$	DS	0.9025	0.1624	0	0	0.3248	0.4872	0.0256
	Improve DS		0.1587	0	0	0.3175	0.4762	0.0476
$E_1 \oplus E_2 \oplus E_3$	DS	0.9677	0.0245	0.0245	0	0.3840	0.5634	0.0036
	Improve DS		0.0688	0.1707	0	0.3191	0.3932	0.0482

be obtained finally.

It shows that the diagnostic capability can be improved by reducing the uncertainty efficiently by fusion reasoning for all the evidences that are not redundant.

The fusion results of the method proposed in this text are not as good as those from D-S evidence theory, according to Tables 4 and 5. Because the former is based on solving the fusion of high conflict evidences ($k \rightarrow 1$) efficiently and it affirms the openness of the recognition framework. The latter can get a good synthetic effect for normal evidences and think the current recognition framework is complete and close. The synthetic result shows that the method with weight factor considered is also effective for solving the synthesis of normal evidences.

5 Conclusion

a. An integrated diagnostic method with evidence theory and rough set fusion reasoning is put forward and it can overcome the problems of subjectivity, dependency and focus element explosion of traditional evidences. It has a significant theoretical significance and practical value.

b. This paper proposed a synthetic method by considering the weight factor. The method can solve the synthetic problems of the evidences with high conflict and is effective for synthesising normal evidences.

c. The application effect of an integrated diagnosis of rough set and evidence theories is proved to be good

with diagnosis examples. With the increase of original sample data, the accuracy of diagnosis will improve. The method proposed in this text can be promoted and applied in the fault diagnosis to other devices if the sample data are large enough.

d. The research of this paper will be further deepened. It will focus on developing artificial intelligence diagnostic system for better application in industrial practice to achieve maximum production benefits in the direction of our subsequent research.

Acknowledgments

The authors acknowledge the grants from the National Natural Science Foundation of China (grant no. 71171198), the Natural Science Foundation of Guangdong Province (2019A151511131) and the Intelligent Manufacturing Comprehensive Standardisation Project (2018) by the Ministry of Industry and Information Technology, P. R. China.

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