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CONDITION MONITORING OF ROLLER BEARING USING ENHANCED DEMPSTER-SHAFER EVIDENCE THEORY

Xingtong Zhu, Minchuan Huang, Ke Chen

School of computer science, Guangdong University of Petrochemical Technology, Maoming, China

Abstract. *According to the generalized Jaccard coefficient and false degree, an improved approach is proposed by incorporating Dempster-Shafer proofs for determining the level of confidence in the evidence. It also determines the weight of proof in terms of trust and falsity. Then, the base probability of the original evidence is weighted and averaged, followed by the adoption of the combined Dempster's compositional rule. It is evident that the above combination can be applied in condition monitoring of bearings up to rupture. Firstly, the supporting vibration signal is decomposed by applying the empirical mode decomposition, empirical wavelet transformation and variational mode decomposition approaches. All the vectors of the fault characteristic are extracted by combining the sample entropy. Then, the fault probability is obtained by performing preliminary diagnosis using the relevance vector machine, where the obtained preliminary diagnostic result is considered as the primary probability of the Dempster-Shafer evidence theory. Finally, it is revealed that an accurate diagnosis could be achieved by performing fusion using the enhanced evidence combination method. Specifically, the accuracies of the initial condition monitoring based on the EMD, EWT and VMD sample entropies and RVM were found to be 97.5%, 98.75% and 95%, respectively. The closeness and high values of these accuracies show that the selected methods are valid. The obtained condition monitoring results show that the relevance vector machine combined with the Dempster-Shafer evidence could enhance the efficiency. This theory has the least error and better reliability in supporting failure diagnosis.*

Key words: *Evidence combination, Generalized Jaccard coefficient, Falsity, Bearing Condition monitoring, Dempster-Shafer (D-S)*

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Corresponding author: Minchuan Huang
School of Computer Science, Guangdong University of Petrochemical Technology, No. 139, Guandu 2nd Road, Maoming City, Guangdong Province: 525000, China
E-mail: h0912259520@163.com

1. INTRODUCTION

A bearing is an important part of rotational components of a machine. The failure of the bearing affects the performance of the machine, leading to power loss, more wear and tear of the machine components, and even to break down of the machine. Since every bearing usually remains around 30% defective, the vibration signals generated from bearings should be monitored continuously. Timely identification and maintenance of bearing defects can ensure the safety of machine components and production personnel. The research on the diagnosis of bearing defects has practical importance to consider the general operations of rotating machine components and safety of operators.

The Dempster-Shafer (D-S) evidence theory [1-3] uses both upper and lower limit probabilities in solving multivalued mapping problems, thus leading to be an inaccurate reasoning theory. Such study is initiated from the Dempster-Shafer evidence theory [1,2]. It is supposed to be an effective method in handling uncertain information, and widely used in information merging, decision-making and many other areas [4-7].

The performance can be enhanced by combining evidences using an average rule. Average the base probability distribution value and use the Dempster combination rules for the N-1 combination [8]. The credibility of evidences is first obtained by measuring the closeness error between them through the Jousselme distance function as per the Murphy's method [9]. Then, the weightage of evidence is determined by combining the average credibility as per the Dempster's combination rule [9].

In this article, a combined method is presented for proving conflict by using the generalized Jaccard coefficient [10-12]. The objective of the present work is to replace the Jousselme distance with the generalized Jaccard coefficient [11]. Both the generalized Jaccard coefficient and Jousselme distance are measures of the distance between two sets of evidence in the Dempster-Shafer theory. However, the generalized Jaccard coefficient is considered superior to the Jousselme distance in several ways: (a) Handles the empty set: The Jousselme distance cannot handle the empty set, which means it is not well-defined when one of the sets is empty. On the other hand, the generalized Jaccard coefficient can handle the empty set and provide a meaningful result in such cases. (b) Reflects uncertainty: The Jousselme distance does not reflect the uncertainty associated with evidence. In contrast, the generalized Jaccard coefficient can reflect the degree of uncertainty in the evidence, which is important in applications where the evidence may be ambiguous. (c) Considers negative evidence: The Jousselme distance does not consider negative evidence, which may be useful in some applications. The generalized Jaccard coefficient can handle both positive and negative evidence, allowing for a more comprehensive analysis of the evidence. (d) Consistent with probability theory: The generalized Jaccard coefficient is consistent with probability theory, which means it satisfies the axioms of probability. This property is important for applications where a probability-like interpretation of evidence is desired. For these reasons, the generalized Jaccard coefficient is considered superior to the Jousselme distance in several ways, making it a more versatile and reliable measure of distance between sets of evidence in the Dempster-Shafer theory. Song et al. [13] proposed a method of combining evidences based on their levels of confidence with falsity.

An accelerated single-value thresholding (ASVT) method was considered in [14] for estimating missing values in large scale problems, which was more efficient than a single-value thresholding (SVT) method. A three-step process was proposed in [15] by combining the weighted conflicting evidence with the credibility and uncertainty data of evidence considered according to the Hellinger distance along with the belief entropy. An extended version of the evidence theory was proposed in [16], with the application to monitor the position of gas pressure in a gas pressure regulation station, for dynamic fusion of time domain information by combining the time decay factor with the relative conflict factor.

An innovative evidential correlation coefficient (ECC) was proposed in [17] for decision making in measuring the conflict distance of a belief function by satisfying various criteria, such as symmetry, non-negativity, insensitivity, boundedness, and extreme consistencies. A combined method of conflict proving, called as the automatic K-means encoder (AE-K means), was proposed in [18], where a composite credibility defined based on an automatic encoder and similarity of evidence integrates both direct and indirect data about the evidence for efficiently obtaining detail data by reducing the involvement of other factors. The D-S evidence theory is used in condition monitoring as an uncertainty algorithm because of its certain benefits.

The back propagation (BP) neural network, widely used as the primary method to enhance the vector machine and radial basis function, was used in [19] for preliminary diagnosis, where three preliminary diagnosis results were combined using an improved D-S evidence theory. A new weighted evidence fusion method was proposed in [20,21] for monitoring bearing conditions.

In [22], features from vibration signals were extracted by using a multi-dimensional feature extraction method that combines entropy feature, Holder coefficient feature and improved generalized box dimension feature; followed by the calculation of the basic belief distribution using the gray correlation algorithm; and finally patterns of defects were recognized by merging the basic belief distribution using the Yager method.

In [23], an enhanced fusion method of the Dempster-Shafer theory of proof was presented for adjusting sensor weights, as per the diagnostic accuracy of different sensor data, by using the kappa coefficient as the closeness error between evidences. The reader is also referred to a recent review by Hakim et al. [24].

It is observed that there is no universally recognized method for combining evidences. Hence, researchers focus on improving such methods based on the D-S evidence theory. Since the weight distribution of the existing evidence is not reasonable enough, more importance should be given to effective methods for combining conflicting evidences. In this article, a method of combining evidences is proposed based on the generalized Jaccard coefficient and false degree, and its effectiveness is demonstrated by diagnosing failure of bearings.

The aim of the study is to propose an improved approach for condition monitoring of bearings up to rupture using the Dempster-Shafer evidence theory and to demonstrate its effectiveness in achieving accurate diagnosis. This paper is written to present a novel approach for condition monitoring of bearings that incorporates the Dempster-Shafer evidence theory and to provide evidence of its efficiency in supporting failure diagnosis. The difference of the present submitted paper from the previous works is the incorporation of the Dempster-Shafer evidence theory for determining the level of confidence in the evidence and weighting the base probability of the original evidence, followed by the adoption of the combined Dempster's compositional rule. This approach is shown to enhance the efficiency, have the least error, and better reliability in supporting failure diagnosis.

2. IMPROVING DEMPSTER-SHAFER (D-S) EVIDENCE THEORY

The Bayesian method, generalized by using the D-S evidence theory, is primarily a mathematical method to cope up with uncertainty by using the Bayesian conditional probability theory. The method needs to know the likelihood probability of a problem in advance. In this case, the D-S evidence theory is more adoptable in handling uncertain data, which can express the uncertainty of a problem without knowing its likelihood probability a priori. In the D-S identification framework, a set of incompatible proposals provide many possible answers, among which one might be the right answer. The concept of "basic probability distribution (BPA)" refers to a subset of the recognition framework and the degree of confidence for each proposal. If the event criteria are met, then the value of the impossible event of the corresponding base probability distribution becomes 0. $m(\phi)=0$ indicates 0 value of the probability distribution for the impossible event. It is described in the confidence function as the total probability corresponding to each subassembly in A. The likelihood function, which represents the uncertainty measure, sums up all the subassemblies BPA that intersect A and the expression of non-repudiation confidence in A. In the Trust space [*Bel(A), pl(A)*], *Bel(A)* represents the lower limit function, and *pl(A)* represents the upper limit function.

$$\sum_{A\subseteq\Theta} m(A) = 1 \tag{1}$$

$$\mathrm{Bel}: 2^{\Theta} \to [0,1] \tag{2}$$

$$\mathrm{Bel}(A) = \sum_{B\subset A} m(B) \;\; (\forall A \subset P) \tag{3}$$

$$\mathrm{pl}(A) = 1 - \mathrm{Bel}(\bar{A}) = \sum_{B\subset P} m(B) - \sum_{B\subset \bar{A}} m(B) = \sum_{B\cap A\neq\phi} m(B) \tag{4}$$

2.1 Dempster Composition Rules

For $\forall A \subseteq \Theta$, the rule given by the Dempster combination of two different mass functions m_1 and m_2 is defined on Θ: K as the conflict coefficient. If there are n finite functions for masses $m_1, m_2, \ldots M_n$ defined on Θ, then their Dempster combination rules can be expressed as follows:

$$m_1 \oplus m_2(A) = \frac{1}{K}\sum_{B\cap C=A} m_1(B)\cdot m_2(C) \tag{5}$$

$$(m_1 \oplus m_2 \oplus \cdots \oplus m_n)(A) = \frac{1}{K}\sum_{A_1\cap A_2\cap\cdots\cap A_n=A} m_1(A_1)\cdot m_2(A_2)\cdots m_n(A_n) \tag{6}$$

$$K = \sum_{A_1\cap\cdots\cap A_2\neq\phi} m_1(A_1)\cdot m_2(A_2)\cdots m_n(A_n) = 1 - \sum_{A_1\cap\cdots\cap A_2=\phi} m_1(A_1)\cdot m_2(A_2)\cdots m_n(A_n) \tag{7}$$

2.2 Evidence Combining Method Based on Generalized Jaccard Factor and False Degree

The generalized Jaccard coefficient, also referred to as the Tanimoto coefficient, is a method of measuring similarity, e.g., the similarities of evidences. In this paper, a method is proposed for combining evidences based on the generalized Jaccard coefficient and false degree. The important points of this method are described below.

- Input the base probabilities of n evidences.
- Calculate the generalized Jaccard coefficient of proof using the following formula:

$$\mathrm{sim}(m_1, m_2) = \frac{\sum_{i=1}^{n} m_1(A_i)\cdot m_2(A_i)}{\sum_{i=1}^{n} m_1(A_i)^2 + \sum_{i=1}^{n} m_2(A_i)^2 - \sum_{i=1}^{n} m_1(A_1)\cdot m_2(A_i)} \tag{8}$$

– Calculate the trust between evidences as follows:

$$\mathrm{crd}_i = \frac{\sup(m_i)}{\sum_{i=1}^{n} \sup(m_i)}\ ; \quad \text{where,}\ \sup(m_i) = \sum_{j=1, j\neq i}^{n} \mathrm{sim}(m_i, m_j) \tag{9}$$

– Calculate the falsehood between evidences using the falsification formula of evidence. The false degree of evidence is a measure of evidence conflict as proposed by Schubert [25]. It is determined according to the conflict coefficient of evidence as expressed by Eq. (10), where K_0 is the global conflict system and K_i is the conflict coefficient between the remaining evidences except m_i. The false degree vector of evidence has n elements, $m_1, m_2, m_3, \ldots, m_n$.

$$F(m_i) = \frac{K_0 - K_i}{1 - K_i}; \quad \text{where,}\ F = [F(m_1), F(m_2), \cdots F(m_n)]^T \tag{10}$$

– The degree of trust and falsehood of evidence are obtained by using the following weight coefficient:

$$w_i = \mathrm{crd}_i + 1 - F(m_i) \tag{11}$$

– The weight coefficient is normalized as follows:

$$\overline{w_i} = \frac{w_i}{\sum_{i=1}^{n} w_i} \tag{12}$$

– After weighting the base probabilities of all the evidences using the normalized weight coefficient, calculate the average value as follows:

$$\mathrm{MAE} = \sum_{i=1}^{n} (\mathrm{crd}_i \times m_i) \tag{13}$$

– Combine weighted average BPA for (n-1) times using the Dempster synthesis rule.

3. Numerical Example

In this paper, we take an example from the efficient combination approach of conflicting evidences for generating data, and set the identification framework as $\Theta=\{f_1,f_2,f_3\}$. In this case, five evidences are involved in the probability distribution, which are given below.

$$\text{E1}: m_1(f_1) = 0.50, m_1(f_2) = 0.2, m_1(f_3) = 0.30$$

$$\text{E2}: m_2(f_1) = 0.00, m_2(f_2) = 0.9, m_2(f_3) = 0.10$$

$$\text{E3}: m_3(f_1) = 0.55, m_3(f_2) = 0.1, m_3(f_3) = 0.35$$

$$\text{E4}: m_4(f_1) = 0.55, m_4(f_2) = 0.1, m_4(f_3) = 0.35$$

$$\text{E5}: m_5(f_1) = 0.55, m_5(f_2) = 0.1, m_5(f_3) = 0.35$$

Table 1 shows the comparison of the methods used to synthesize evidences.

Table 1 Comparison of methods used in evidence synthesis.

Item	$m(f_1)$	$m(f_2)$	$m(f_3)$
Bisht and Kumar [2]	0.0000	0.1228	0.8772
Deng [10]	0.7958	0.0932	0.1110
Song [13]	0.9636	0.0109	0.0255
Present methodology	0.9703	0.0048	0.0249

4. BEARING CONDITION MONITORING

The proposed D-S evidence theory method for condition monitoring of bearings includes two main steps: construction of evidence body and combining evidences.

4.1 Condition Monitoring Model Based on Enhanced D-S Evidence Theory

Data of the vibration signals of rolling contact bearings is used for monitoring bearing conditions. Direct extraction of effective information affects the accuracy of condition monitoring. In order to avoid this problem, inaccurate signals are filtered out by using a single-signal decomposition method. In this paper, the empirical mode decomposition (EMD), empirical wavelet transformation (EWT) and variable mode decomposition (VMD) approaches are used for this purpose. The characteristic information of rolling contact bearings is extracted from their signals generated due to vibration by combining the sample entropies using the relevance vector machine (RVM). This information is used for enhancing the preliminary diagnosis by improving the evidence theory. Figure 1 depicts the structure of the diagnosis model. Specifically, calculations of sample entropy are performed for each of the three methods, followed by mRVM fault diagnosis. Thereafter, fusion diagnosis was carried out on the basis of the improved D-S evidence theory. Finally, the final diagnosis results are extracted based on the decision rules.

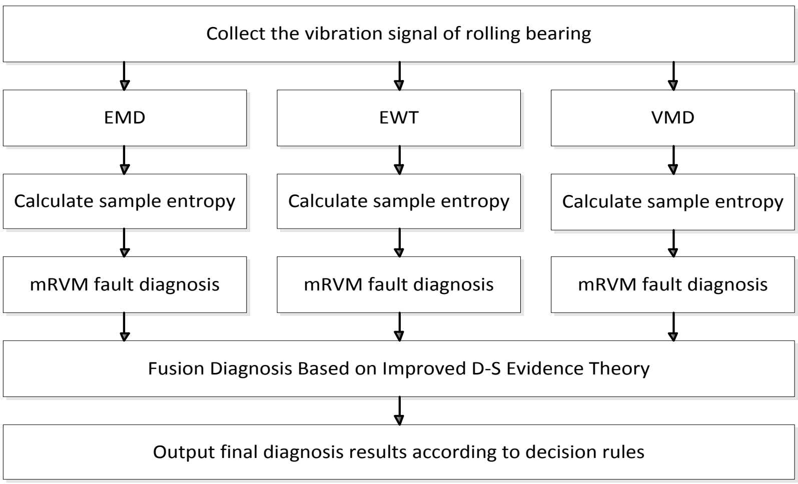

Fig. 1 Methodology for condition monitoring of bearings by using enhanced D-S evidence theory

4.2 Diagnosis of Condition Monitoring Mode

The condition monitoring mode is diagnosed in the following steps:

- Collection of vibration signal of rolling contact bearing. The vibration signals of the inner race, outer race and rolling element in both fault and normal states are collected by an acceleration sensor.
- Feature extraction. The wavelet packet, empirical mode decomposition, and VMD approaches are used for calculating the sample entropy of signal components by suppressing their vibration signals.
- Probability is determined by performing preliminary diagnosis using the correlation vector machine.
- The input of evidence fusion is obtained in the form of fault probability by performing preliminary diagnosis using RVM, and then the evidence combination method based on similarity and falsehood is used to fuse the evidence bodies, so as to obtain the fused probability and finally to complete the condition monitoring.

5. Experiment and Result Analysis

The data used in this work was derived from the Bearing Data Center of Case Western Reserve University, United States [26]. The schematic of the test bench used for collecting experimental data is shown in Figure 2, which is mainly composed of a 1.5KW motor, a decoder and a power tester. The drive-end of the motor is equipped with a bearing (model: SKF6205), and the fan-end is also equipped with another bearing (model: SKF6203).

The vibration signal of the rolling contact bearing is measured using an acceleration sensor, which is installed at the drive-end of the motor. The measurement includes the vibration signals of the inner race, outer race and rolling element in both fault and normal states. In this experiment, 2048 sample data points were collected, including 100 samples of vibration signals for each bearing state.

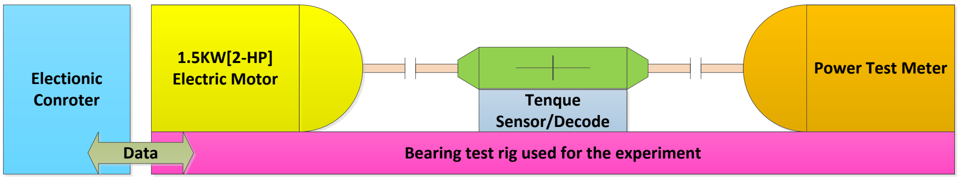

Fig. 2 Schematic of the experimental bearing test rig.

5.1 Collection of Vibration Data of Rolling Contact Bearing

The bearing data used in this paper is the vibration data acquired by the acceleration sensor positioned at the drive-end of the motor. Data is collected in different states, including the normal state (NC), IRF, ORF and RBF. The experimental data reveals that the combination of RVM and D-S evidence theory could more precisely complete the condition monitoring of the rolling contact bearing. Figure 3 shows the amplitude of the acceleration signals.

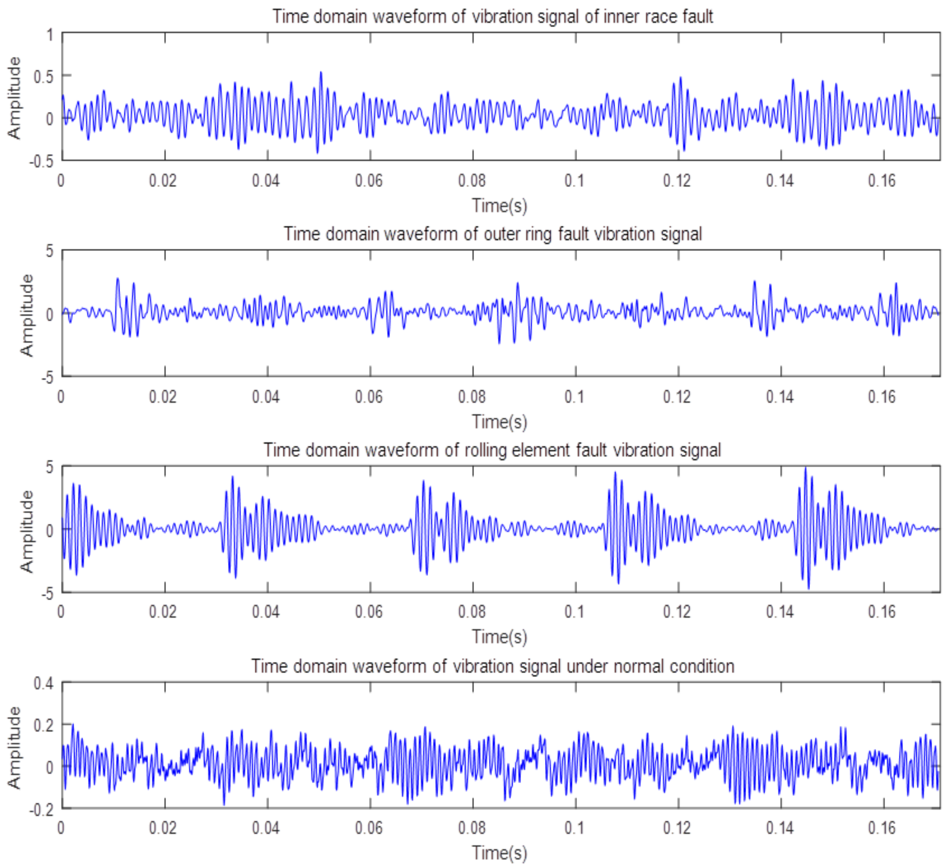

Fig. 3 Experimental data of amplitude of vibration of (a) IRF (b) ORF and (c) RBF. (d) Vibration signal under normal condition

5.2 Feature Extraction

After breaking down the vibration signal by the EMD, EWT and VMD approaches, the sample entropy of the signal component is computed. Then, three characteristic subspaces are constructed as the input of the correlation vector.

Figures 4 to 6 show the waveforms of the component signals of the faulty inner race decomposed by the EMD, EWT and VMD methods.

The sample entropies corresponding to the component signals obtained by the EMD, EWT and VMD decomposition methods, as shown in Figures 4-6, are [0.5728, 0.5814, 0.3126, 0.1925, 0.0633], [0.4603, 0.5997, 0.3063, 0.2776, 0.4518] and [0.5902, 0.5938, 0.5663, 0.1034, 0.4921], respectively.

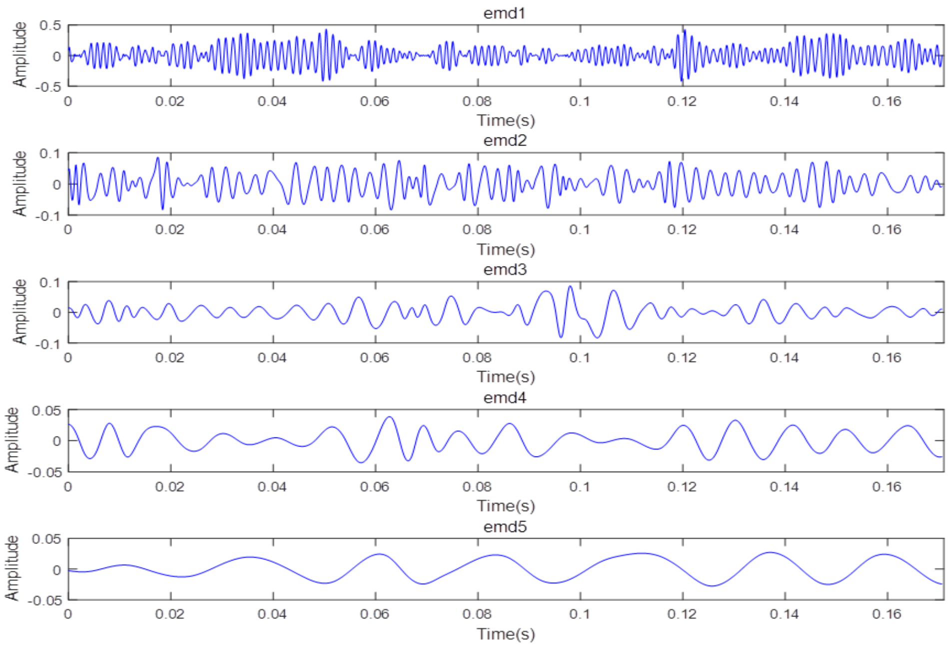

Fig. 4 Transformed waveforms of the original signals obtained by EMD method

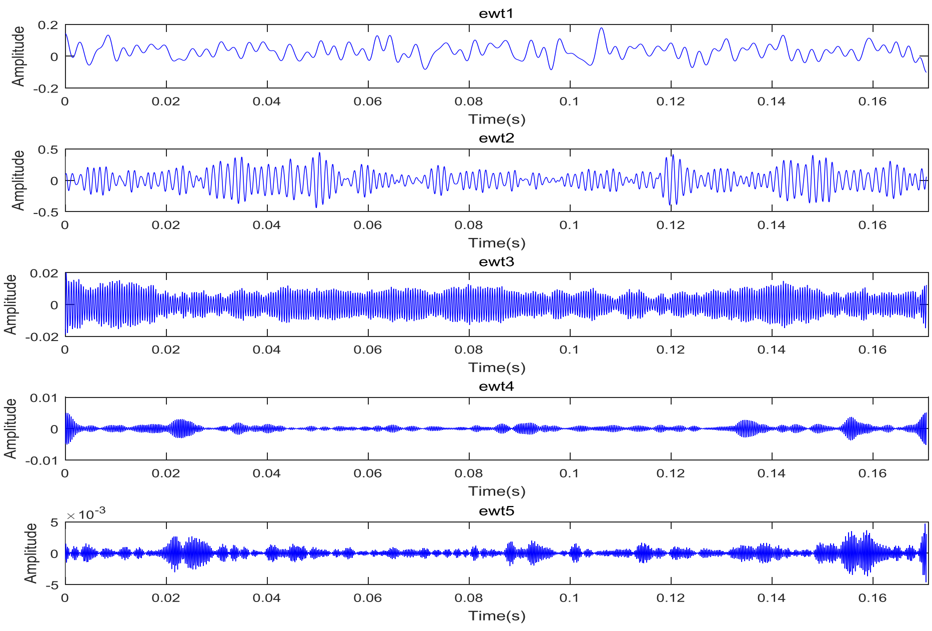

Fig. 5 Transformed waveforms of the original signals obtained by EWT method

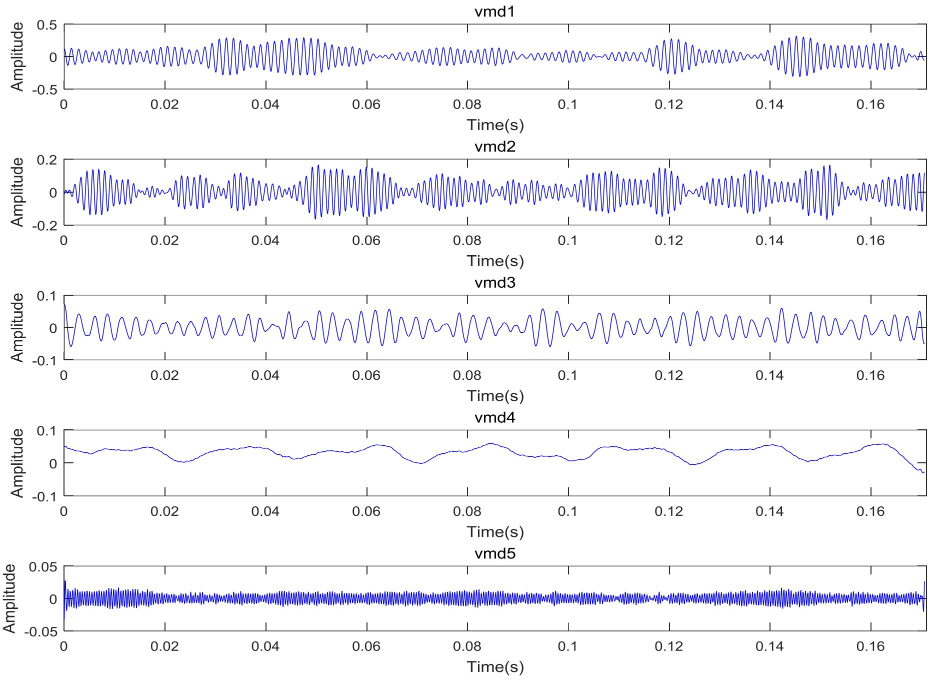

Fig. 6 Transformed waveforms of the original signals obtained by VMD method

5.3 Preliminary Diagnosis Results by Vector Machine

For the purpose of diagnosis, the output probability is obtained by using the relevance vector machine. Tables 2 to 4 present the preliminary condition monitoring results for few test samples obtained by the RVM method.

Table 2 Results of EMD sample entropy and RVM condition monitoring

Test sample No	Rolling element failure probability	Failure probability of inner ring	Failure probability of outer ring	Normal state probability	Test label	Actual label
1	0.9981	0.0000	0.0013	0.0006	1	1
3	0.3573	0.0412	0.0002	0.6012	4	1
4	0.9906	0.0000	0.0062	0.0032	1	1
14	0.9785	0.0000	0.0027	0.0189	1	1
17	0.9582	0.0000	0.0000	0.0418	1	1
19	0.9830	0.0000	0.0168	0.0001	1	1
43	0.5485	0.0000	0.4351	0.0164	1	3
56	0.0408	0.0001	0.9480	0.0112	3	3

It can be seen that the rolling element failure probability in Tables 2 and 3 appear to be approximately inverse to the failure probabilities of the outer and inner rings, respectively, while no correlation was observed in Table 4. These preliminary results are useful in elucidating the observations in the next sub-section and Table 5.

Table 3 Results of EWT sample entropy and RVM condition monitoring

Test sample No	Rolling element failure probability	Failure probability of inner ring	Failure probability of outer ring	Normal state probability	Test label	Actual label
1	0.9160	0.0834	0.0006	0.0000	1	1
3	0.7632	0.2368	0.0000	0.0000	1	1
4	0.4653	0.5315	0.0032	0.0000	2	1
14	0.8586	0.1176	0.0000	0.0238	1	1
17	0.9920	0.0079	0.0000	0.0001	1	1
19	0.9745	0.0255	0.0000	0.0001	1	1
43	0.0000	0.0012	0.9983	0.0006	3	3
56	0.0002	0.0036	0.9962	0.0000	3	3

Table 4 Results of VMD sample entropy and RVM condition monitoring

Test sample No	Rolling element failure probability	Failure probability of inner ring	Failure probability of outer ring	Normal state probability	Test label	Actual label
1	0.9996	0.0003	0.0001	0.0000	1	1
3	0.9982	0.0000	0.0018	0.0000	1	1
4	0.9998	0.0000	0.0002	0.0000	1	1
14	0.1517	0.0001	0.8482	0.0000	3	1
17	0.4605	0.5260	0.0135	0.0000	2	1
19	0.0551	0.5337	0.4112	0.0000	2	1
43	0.0018	0.1450	0.8531	0.0000	3	3
56	0.4336	0.1355	0.4309	0.0000	1	3

5.4 Final Diagnosis Results by Improved Evidence Combination Method for Fusion

Preliminary diagnosis is performed by RVM, where the failure probability is obtained as the evidence. The final diagnosis is performed by the method based on the combination of the generalized Jaccard coefficient and false degree, where each evidence body is fused to obtain the probability to be used in condition monitoring. Table 5 shows the evidence of this combination method, and the results of the combined evidences are shown in Tables 2-4.

A total of 80 test samples were considered in this experiment, 20 samples in each state. The accuracies of the initial condition monitoring based on the EMD, EWT and VMD sample entropies and RVM were found to be 97.5%, 98.75% and 95%, respectively. Finally, the enhanced D-S evidence combination procedure was employed for fusion to complete the diagnosis.

Table 5 Condition monitoring results obtained by the proposed fusion method

Test sample No	Rolling element failure probability	Failure probability of inner ring	Failure probability of outer ring	Normal state probability	Test label	Actual label
1	1.0000	0.0000	0.0000	0.0000	1	1
3	0.9954	0.0018	0.0000	0.0028	1	1
4	0.9982	0.0018	0.0000	0.0000	1	1
14	0.9993	0.0002	0.0005	0.0000	1	1
17	0.9979	0.0021	0.0000	0.0000	1	1
19	0.9999	0.0000	0.0000	0.0000	1	1
43	0.0025	0.0003	0.9972	0.0000	3	3
56	0.0018	0.0000	0.9982	0.0000	3	3

6. CONCLUSION

In this paper, taking rolling contact bearing as the object, bearing fault features are studied by different methods, and then the relevant vector machine is used to determine the probability. Finally, the types of faults are identified by using an improved method based on the D-S evidence theory for fusion, which does not figure out the fundamental probability distribution. The probability obtained by RVM is applied as the BPA value, and then the enhanced evidence combination method is applied to diagnose the bearing fault. Compared with a single method, the diagnosis of the proposed method was found more accurate and reliable.

In conclusion, the proposed approach that incorporates Dempster-Shafer proofs for determining the level of confidence in evidence and determining the weight of proof in terms of trust and falsity has shown promising results in condition monitoring of bearings up to rupture. The combination of the relevance vector machine and the enhanced evidence combination method based on the generalized Jaccard coefficient and false degree has enhanced the efficiency and achieved accurate diagnosis with the least error and better reliability in supporting failure diagnosis. The experiment's results on 80 test samples with different states have shown high accuracies of the initial condition monitoring based on the EMD, EWT, and VMD sample entropies and RVM. Finally, the enhanced D-S evidence combination procedure was employed for fusion to complete the diagnosis. Overall, this approach provides a new perspective for condition monitoring that can improve the diagnosis and reliability of the system.

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