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AIRCRAFT SECURITY ENHANCEMENT: ROTATING MACHINERY FAULT DIAGNOSIS AND HEALTH ASSESSMENT USING MANIFOLD LEARNING AND DYNAMIC TIME WARPING

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Abstract

To enhance the ability of AHMS, a research on aircraft rotating machinery fault diagnosis and health assessment techniques is conduct, and an approach combining manifold learning and dynamic time warping (DTW) is present in this paper. First, the original nonlinear and nonstationary vibration signals are processed by wavelet packet decomposition, and the wavelet energies are extracted to act as fault features, which are high-dimensional. Then, manifold learning method is employed for dimensionality reduction to find the intrinsic fault features. Finally, based on the accurate fault features, DTW is introduced to determine the fault state and assess the heath degree. The results of fault diagnosis and health assessment for a self-priming centrifugal pump in the aircraft fuel injection system demonstrate the effectiveness of the proposed approach.

1 Introduction

Aircraft health management system (AHMS), which can detect and diagnose faults, assess and predict health degradation trends, is important to assure the security of aircrafts and help make proper maintenance decisions so as to reduce the operation and maintenance costs [1-3]. As an important part of aircrafts, rotating machinery is a vital object in AHMS. An unexpected failure of rotating machinery may cause a sudden breakdown of AHMS, leading to enormous financial losses or even personnel casualties [4-6]. As for rotating machinery, the monitorable signals are mostly the nonlinear and nonstationary vibration signals [7, 8], from which the effective fault features are difficult to be extracted, thus making the results of fault diagnosis and health assessment unsatisfactory. Hence, high-dimensional features from multi scales are usually extracted in case missing any useful fault information [9-11]. Wavelet packet transform (WPT), with the ability of arbitrary time–frequency resolution, provides an effective way to process nonlinear and nonstationary vibration signals [5, 12, 13], and the wavelet energies of the decomposed components contains multi-scale fault information [14]. Thereout, WPT is employed to decompose the original vibration signals and the wavelet energies are calculated as the fault features in this paper.

The high-dimensional fault features help to contain abundant fault information, but conversely, they are apt to cause information redundancy and bring more burdens for algorithms of diagnosis and assessment [10, 11]. To solve this dilemma, methods for nonlinear dimensionality reduction are needed. Manifold learning, famous for nonlinear dimensionality reduction, is proven to be effective in face recognition[15], hyperspectral image processing [16], and text document classification/search [17, 18]. Thus, in this paper, manifold learning methods are applied for obtaining low-dimensional and differentiable fault features.

For fault/health states determination, the key is to measure the matching or deviation degree between the samples under test with the template samples. Dynamic time warping (DTW), first proposed for speech recognition [19], is a popular pattern match technique and has been applied in many fields, such as fingerprint verification [20], human motion recognition [21], and online signature verification [22]. Thus, DTW is introduced for fault diagnosis and health assessment in this paper.

The outline of this paper is as follows. Section 2 introduces the methods of WPT with wavelet energy, manifold learning, and DTW. Then in Section 3, a fault diagnosis and health assessment framework is built and experimentally validated using vibration signals from a self-priming centrifugal pump in the aircraft fuel injection system. Finally, conclusions are drawn in Section 4.

2 Methodology

2.1 Wavelet packet transform and wavelet energy

WPT, an expansion of the wavelet transform, has a better frequency resolution for the decomposed signal, which makes WPT popular in signal processing [14]. With the use of WPT, the original signal can be decomposed repeatedly into successive low and high frequency components, depending on a recursive filter-decimation operation [12, 13].

As in different health states, the vibration intensity in the same frequency band is different, thus the wavelet energy of each component can be calculated to act as the fault feature. Set three-level WPT as an example, the eight wavelet-band energy values are calculated as followed:

$$E_{3j} = \int \left|S_{3j}(t)\right|^2 dt = \sum_{k=1}^{n} \left|x_{jk}\right|^2 \qquad (1)$$

where, x_{jk} (j=0,1,…,7, k=1,2,…,n) denotes the amplitude of reconstructed signal S_{3j}. Then, for each health state, the fault feature vector can be formed by the eight wavelet energy values.
More details about WPT and wavelet energy can be found in Ref.[23].

2.2 Manifold learning

In 2000, Seung and Lee published their research report named "The manifold ways of perception" in Science [24], which opens the floodgates to the research of manifold learning methods. The main application of manifold learning is dimensionality reduction, and many methods has been proposed, including linear and nonlinear methods, such as kernel principal component analysis (KPCA), Laplacian Eigenmaps (LE), local linear embedding (LLE), Hessian LLE (HLLE),local tangent space alignment (LTSA), and linear local tangent space alignment (LLTSA). The essence of these methods is to find low-dimensional manifold structure in the high-dimensional data space, while guaranteeing the error between low-dimensional data and high-dimensional data minimal. In this paper, the above six methods are all used for fault feature dimensionality reduction so as to make a comparison and find the best one. The detailed descriptions of most manifold learning methods can be found in Ref.[25].

2.3 Dynamic time warping

The algorithm principle of DTW can be described as follows. For two sequences C=c_1,…, c_i,…, c_m and Q=q_1,…,q_j,…, q_n, distances between corresponding elements can be calculated as $d(C_i,Q_j)$ by a Euclidean distance, thus forming a $n \times m$ distance matrix. Then, the warping path U = (u_1,…,u_k,…, u_L) through the matrix can be determined by forcing the cumulative distance minimal, where $\max(m,n) \le L \le m+n-1$. The path should satisfy some local constraints as described in Ref.[19].Finally, the DTW distance is defined as [26, 27]:

$$DTW(C_i,Q_j) = d(C_i,Q_j) + \min\begin{cases} DTW(C_i,Q_{j-1}) \\ DTW(C_{i-1},Q_j) \\ DTW(C_{i-1},Q_{j-1}) \end{cases} \qquad (2)$$

2.4 Approach for fault diagnosis and health assessment

The approach proposed in this paper is shown in Fig. 1 and described as follows.

(1) Each signal is decomposed by three-level WPT, thus obtaining eight sub-components.

(2) The wavelet energy of each sub-component is calculated to form the high-dimensional fault feature vector.

(3) Six manifold learning methods are used to reduce feature dimensionality and obtain more differentiable and stable fault features.

(4) Based on the compact fault features, DTW is introduced to diagnose the fault state and assess the health degree.

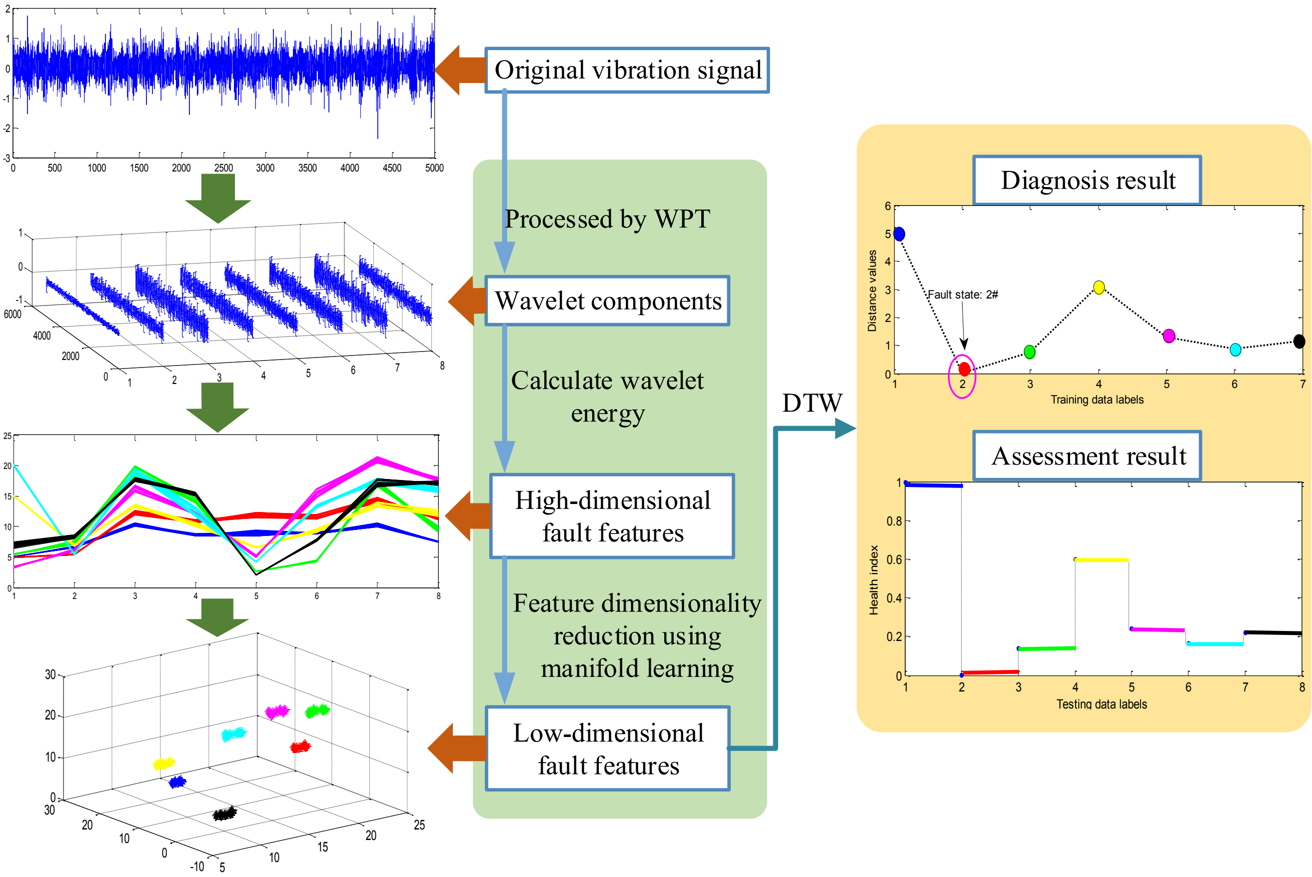

Fig. 1. Flow Chart of the Proposed Approach.

3 Case study

3.1 Experiment data source

The vibration signals from a self-priming centrifugal pump in the aircraft fuel injection system are used as the experimental raw data to demonstrate the effectiveness of the proposed approach. The test rig is built as shown in Fig.2, in which an acceleration sensor installed right above on the motor shell. The collected signals belong to seven health states, namely normal, bearing faults of inner, outer, rolling element, mixed faults of bearing inner and impeller, bearing outer and impeller. And the data of each health state contains 20 groups, the acquisition time of each group lasts 2 s, and the sampling interval is 5s with a sampling frequency of 10.24 kHz. For example, the original vibration signal of normal state is shown in Fig.3.

Fig. 2. The Test Rig of Data Acquisition.

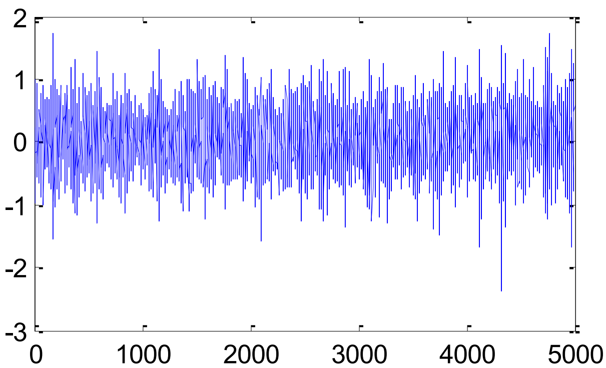

Fig. 3. Vibration Signal of Normal State.

3.2 Feature extraction by WPD and manifold learning

3.2.1 Signal decomposition based on WPT

To acquire the fault features, three-level WPT is firstly applied to decompose signals into eight sub-components, as shown in Fig.4, so as to reveal fault information in multi-scales. Each group of signal contains 5000 points.

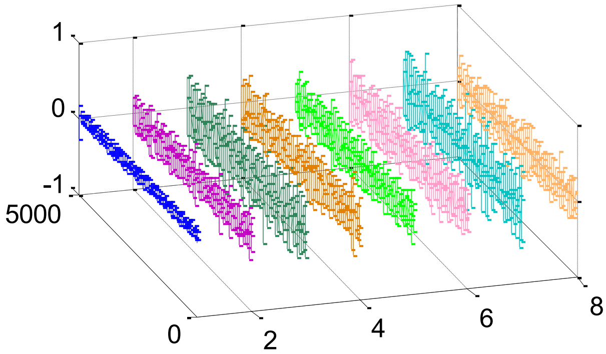

Fig. 4. Signal Decomposition Result by WPT.

3.2.2 Calculate the wavelet energy features

Then, the wavelet energy value of each sub-component is calculated to form the eight-dimensional feature vector. To show the separability among features under different states, a line chart contains seven-state features is drawn in Fig.5, and each state represent by 20-group features. From this chart, we can see that, as the features are high-dimensional, the separability between different states is difficult to judge, and the complex feature vectors are detrimental for the subsequent fault diagnosis and health assessment methods.

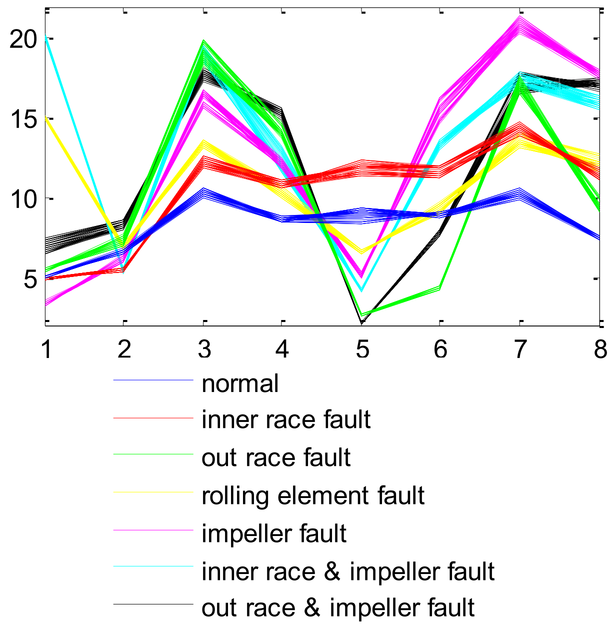

Fig. 5. Line Chart of Different Health State Features.

3.2.3 Features dimensionality reduction by manifold learning

As analyzed above, the high-dimensional features not only contains useful fault information, they also contains some redundant information, which burdens the subsequent algorithms. Thus, manifold learning methods are employed to reduce the feature dimensionality, so as to obtain more stable and differentiable low-dimensional features. In order to find a better method from the many manifold learning methods, six typical methods, KPAC, LE, LLE, HLLE, LTSA, LLTSA, are compared together. The dimensionality reduction results are shown in Fig.6, from which we can see that, LLTSA is the better one among the six methods while others exist promiscuous features, and the three-dimensional features of different health states obtained by LLTSA are obviously differentiable, which lays a good foundation of the subsequent analysis.

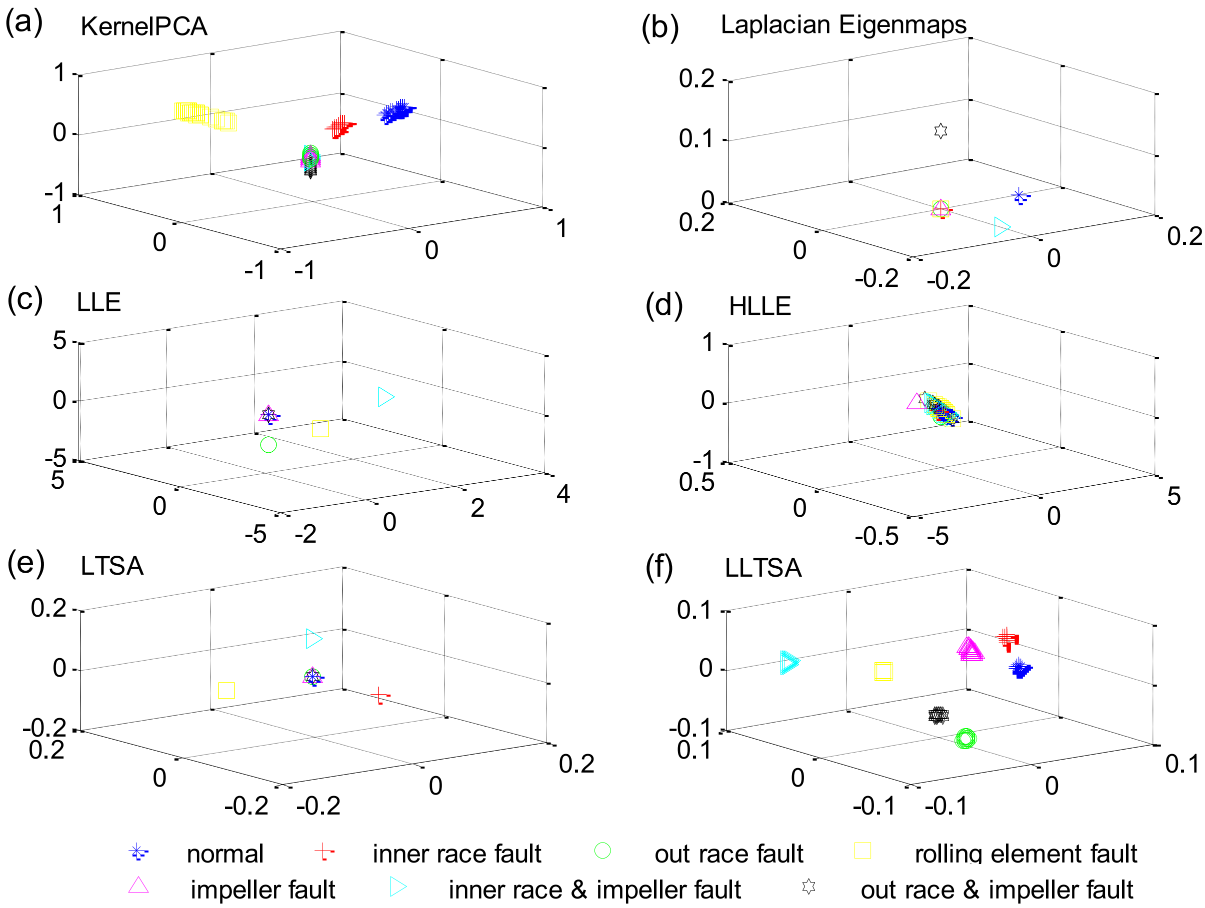

Fig. 6. The Dimensionality Reduction Results by KPCA, LE, LLE, HLLE, LTSA, LLTSA.

3.3 Fault diagnosis and health assessment based on DTW

Based on the stable, differentiable low-dimensional features obtained by WPT and LLTSA, DTW is introduced to diagnose the fault state and to assess the health degree.

3.3.1 Fault diagnosis based on DTW

In fault diagnosis, DTW is used to measure the distance between the testing samples with the training sample set. As mentioned above, the whole signals are from seven health states, thus, the training sample set contains data of seven labels. Each sample of testing or training contains 5-groups feature vectors. For each test sample, distance values to the seven training sample are calculated so as to find the most similar one, then the label of the test sample is the same with the label of the most similar training sample. Thereout, the state of test sample can be determined. As shown in Fig.7, the test sample is close to the training sample of the same label, and away from the different labels.

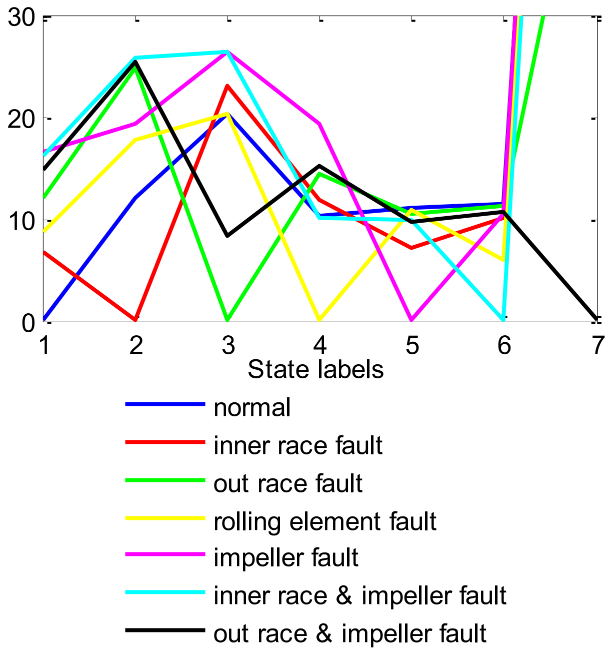

Fig. 7. The results of fault diagnosis by DTW.

3.3.2 Health assessment based on DTW

In health assessment, DTW is applied to measure the distance between the testing samples with the template sample of normal state. The larger distance means the higher health degradation degree, which can precisely assess the current health degree.

Let the calculated distance as d_i, we define the health degree as $R = 1/(d_i + 1)$, and set the health degree of normal state as one. Thereout, the health degree of any state can be calculated.

To demonstrate the effectiveness of the method, a template sample set containing features of seven health state is built, and each sample contains 5-groups feature vectors. Then, for testing sample from one of the seven states, health degree is calculated, as shown in Fig.8, from which we can see that, for normal features, the calculated health degree is one, while for faulty features, the calculated health degree is between one and zero. With using DTW, the health degree of different state samples is shown distinctly.

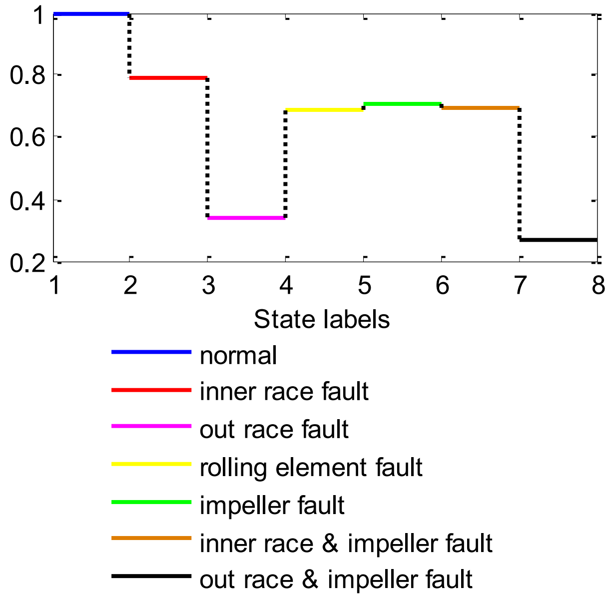

Fig. 8. The results of health assessment by DTW.

4 Conclusions and future works

Aiming at enhancing the ability of AHMS, an approach combining WPT, manifold learning and DTW is proposed for fault diagnosis and health assessment of rotating machinery.

In this paper, with using WPT and wavelet energy, multi-scale features are extracted and abundant fault information are revealed. Then, with the help of manifold learning, more stable and differentiable low-dimensional fault features are obtained. Finally, based on the effective feature vectors, DTW is successfully applied for fault diagnosis and health assessment, making the process more distinct and easier to operate.

The experimental results indicate that the proposed approach is suitable and efficient for fault diagnosis and health assessment of the centrifugal pump, and shows great promise for applications in other aircraft rotating machinery. Future experiments should be done on other aircraft rotating machinery to demonstrate the expandability of the proposed approach.

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