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Mechanical Fault Diagnosis Based on LMD-Approximate Entropy and LSSVM

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Abstract

Mechanical fault diagnosis is a feature extraction and pattern recognition process. The feature extraction is related to the accuracy of fault diagnosis and the reliability of the prediction. How to extract fault features effectively and build an accurate model to recognize fault is the key of diagnosis technology. Accordingly, a feature extraction method based on LMD-approximate entropy was proposed, and combined it with LSSVM to diagnose mechanical fault. Firstly, the decomposition of fault feature by LMD, and then the approximate entropy of product function were taken to extract fault features accurately. Finally, the eigenvectors were input to LS-SVM for fault recognition. Compared with EMD and wavelet decomposition, the results show that it can extract fault features effectively and can improve the accuracy and speed of fault diagnosis.

***Key words**: fault diagnosis, local mean decomposition, approximate entropy, feature extraction, LS-SVM*

1. Introduction

It is difficult to diagnose fault due to the complexity of the mechanical equipment, which result in downtime, other losses and even serious human casualties. The most important feature of the mechanical fault is complexity and multilevel nature [1]. What's more, there are a lot of non-stationary components in fault signals. How to extract fault features from the complex state behavior and recognize it is the key problem of diagnosis technology [2]. Local mean decomposition (LMD) is a new kind of adaptive non-stationary signals analysis method proposed by Jonathan S. Smith. It can decompose adaptively a complex non-stationary signal into a set of components of production function which have physically meaningful instantaneous frequency [3]. Some scholars have studied and compared the EMD and LMD, the result show that the LMD method is superior to the EMD method in mechanical fault diagnosis [4,5]. Therefore, LMD is selected to decompose fault signal in this paper. Approximate Entropy (ApEn) is used to measure the complexity of time series and it is proposed by Steven M Pincus in the early 1990s [6]. Reference [7] studied the engineering applications of approximate entropy in the field of machinery condition monitoring and fault diagnosis. Reference [8] pointed out that the approximate entropy contained more information in the characterization of the dynamics of the signal than the correlation dimension. Therefore, the approximate entropy of PFs was taken to extract fault features in this paper. Support vector machine (SVM) is a machine learning method developed on the basis of statistical learning theory and structural risk minimization. SVM can solve not only the small sample size problem, but also the high-dimensional and local extreme problem compared with neural network algorithm [9]. Otherwise, the structure is also very simple. Due to the above advantage, it has become a hot research at home and abroad [10]. In this paper, the LMD will combine with approximate entropy to extract fault features, and then the approximate entropy of PFs were input into LS-SVM for fault recognition in order to improve the performance of fault diagnosis.

2. Research Method

2.1. LMD

LMD can decompose adaptively a complex signal which with multiple instantaneous frequency components into a set of components of production function which with non-negative

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and physically meaningful instantaneous frequency. Each of PFs is obtained by multiplying the envelope signal and the pure frequency modulated signal. Furthermore, the envelope signal is the instantaneous amplitude of PFs and the instantaneous frequency can be obtained by the pure frequency modulated signal of PFs. After combining the instantaneous amplitude and instantaneous frequency of the PFs, the completed time-frequency distribution of the original signal can be obtained. For any signals $x(\mathrm{t})$,it can be decomposed as follows [11]:

(1) Seek the local mean function $m_{11}(\mathrm{t})$. Find all the local extreme of the original signal $x(\mathrm{t})$ and marketed n_1, n_2, …, n_i …, the local mean function m_i of each two successive extreme can be calculated by

$$\mathrm{m}_i = (\mathrm{n}_i + \mathrm{n}_{i+1})/2 \quad (1)$$

Smooth the local mean function m_i using moving average. If the adjacent point values are equal, it will move average again until any adjacent points are no longer equal。Then the local mean function $m_{11}(\mathrm{t})$ can be formed.

(2) Seek the local envelope function $a_{11}(\mathrm{t})$. The local mean envelope function a_i of each two successive extreme can be calculated by

$$a_i = |n_i - n_{i+1}|/2 \quad (2)$$

Smooth the local envelope function a_i using moving average. If the adjacent point values are equal, it will move average again until any adjacent points are no longer equal。Then the local envelope function $a_{11}(\mathrm{t})$ can be formed.

(3) Subtract the local mean function $m_{11}(\mathrm{t})$ from the original signal.

$$h_{11}(\mathrm{t}) = \mathrm{x}(\mathrm{t}) - \mathrm{m}_{11}(\mathrm{t}) \quad (3)$$

(4) Demodulating $h_{11}(\mathrm{t})$.Dividing $h_{11}(\mathrm{t})$ by $a_{11}(\mathrm{t})$ to get $s_{11}(\mathrm{t})$.

$$s_{11}(\mathrm{t}) = h_{11}(\mathrm{t})/a_{11}(\mathrm{t}) \quad (4)$$

Ideally, $s_{11}(\mathrm{t})$ is a pure frequency modulated signal, viz its local envelope function should satisfy $a_{12}(\mathrm{t})=1$.If $a_{12}(\mathrm{t}) \neq 1$, then the above procedure needs to be repeated until $\mathrm{s}_{1n}(\mathrm{t})$ is a purely frequency modulated signal. In other words, its local envelope function should satisfy $\mathrm{a}_{1(\mathrm{n}+1)}(\mathrm{t})=1$.

(5) Seeking the envelope signal of PFs. Multiplying all the local envelope functions that are obtained during the iterative process to get $a_1(\mathrm{t})$

$$a_1(\mathrm{t}) = a_{11}(\mathrm{t})a_{12}(\mathrm{t})...a_{1n}(\mathrm{t}) = \prod_{q=1}^{n} a_{1q}(\mathrm{t}) \quad (5)$$

(6)Obtain the first product function PF_1 of the original signal. Multiply the envelope signal $a_1(\mathrm{t})$ by the pure frequency modulated signal $\mathrm{s}_{1n}(\mathrm{t})$ to get PF_1.

$$PF_1(t) = a_1(\mathrm{t})\,\mathrm{s}_{1n}(\mathrm{t}) \quad (6)$$

(7)Subtract $PF_1(t)$ from the original signal $x(\mathrm{t})$ and obtain a new signal $\mathrm{u}_1(\mathrm{t})$

$$\mathrm{u}_1(\mathrm{t}) = x(t) - PF_1(t) \quad (7)$$

Take $u_1(t)$ as the new signal and repeat above all procedure k times until $u_k(t)$ becomes monotonic function. Thus, the original signal $x(t)$ is decomposed into k-product and a monotonic function $u_k(t)$.

$$x(t)=\sum_{p=1}^{k} PF_p(t)+u_k(t) \quad (8)$$

From all of above, it is a gradual process which removes the high-frequency component of the signal and does not cause the loss of the original signal.

2.2 Approximate Entropy Algorithm

Approximate entropy can reflect the complexity of a time series. It is used to characterize the probability of the new model of the signal, the more complex signals, the approximate entropy would greater. It can be calculated as follows [12]:

Assume that an original time sequence is $x(1), x(2), ...x(N)$,and the number totals N

(1) M-dimension vectors $X(i)$ can be reconstructed as follows：

$$X(i)=\left[x(i), x(i+1), ...x(i+m-1)\right] \quad (9)$$

where $i=1 \sim N-m+1$

(2) Calculate the distance between $X(i)$ and $X(j)$

$$d(i,j)=\max_{1\text{-}m\text{-}1}\left[\left|x(i+k)\text{-}x(j+k)\right|\right] \quad (10)$$

(3) Given the threshold values of r, where $r>0$,calculate both the number of $d(i,j)$ which is smaller than r and its ratio to $N\text{-}m+1$,defined as $C_i^m(r)$.

$$C_i^m(r)=\frac{1}{N-m+1}\{[d(i,j)<r]\text{'s number}\} \quad (11)$$

(4) First logarithmic for $C_i^m(r)$, and then averaged for all i, defined as $\Phi^m(r)$:

$$\Phi^m(r)=\sum_{i=1}^{N\text{-}m+1}\ln C_i^m(r)\Big/(N\text{-}m+1) \quad (12)$$

(5)Dimension plus 1 and repeat above procedures (1)-(4) to obtain $\Phi^{m+1}(r)$.

(6) Theoretically, ApEn of the original time series is determined as follows:

$$ApEn(m,r)=\lim_{N\to\infty}\left[\Phi^m(r)\text{-}\Phi^{m+1}(r)\right] \quad (13)$$

In practice, when N is a finite value, the approximate entropy is estimated to be as follows:

$$ApEn(m,r,\ N)=\Phi^m(r)\text{-}\Phi^{m+1}(r) \quad (14)$$

Generally, ApEn is calculated with the following proviso: $m=2$, $r=0.1\sim0.2SDx$ (SDx is the standard deviation of original data series $x(i)$). The ApEn is used to the field of fault diagnosis to characterize the complexity and the probability of the new model of the signal. In this paper, combined with LMD decomposition, the ApEn of PFs is calculated to extract fault features accurately.

2.3. LSSVM Classification Algorithm

The main idea of the SVM training is that mapping the nonlinear function of input space into the linear function of a so-called higher dimensional space, Based on nonlinear function SVM, In LSSVM one transform equality constraints into inequality constraints and a sum squared error (SSE) cost function is used in objective function. Given a training data set of N points $\{(x_i, y_i)\} i=1,2,...,N$ with input data x_i and output data y_i.The objective optimization function of LSSVM as follows [9] [13]:

$$\begin{cases} \min J(w,\varepsilon) = \frac{1}{2} w^T w + \frac{1}{2} f \sum_{i=1}^{n} \varepsilon_i^2 \\ \text{s.t. } y_i \left[w^T \varphi(x_i) + b \right] = 1 - \varepsilon_i, (i = 1,...,n) \end{cases} \quad (15)$$

where w is weight vector, ε is error variables, f is positive real constant, b is bias term, $\varphi(x)$ is a nonlinear function which maps the input space sample x into a so-called higher dimensional feature space,

One defines the Lagrangian

$$L(w,b,\varepsilon,\alpha) = J(w,\varepsilon) - \sum_{i=1}^{n} \alpha_i \left\{ y_i \left[w^T \varphi(x_i) + b \right] - 1 + \varepsilon_i \right\} \quad (16)$$

where α_i are Lagrange multipliers. According to Karush Kuhn Tucher(KKT) optimal conditions, w and ε are eliminated to obtain the solution

$$\begin{bmatrix} 0 & l^T \\ l & K + f^{-1} I \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \quad (17)$$

where $l = [1,1,\cdots 1]_{1\times n}^T$, I is unit matrix. one can transform the optimization problem into a problem of solving the linear set of equations. The obtaining classification decision function becomes

$$f(x) = \text{sgn} \left[\sum_{i=1}^{n} \alpha_i K(x, x_i) + b \right] \quad (18)$$

where $K(x,x_i) = \exp\left\{ \|x - x_i\|^2 / \delta^2 \right\}$ is RBF kernel function, δ is the width coefficient of the kernel function.

3. Results and Analysis

3.1. The feature extraction of fault signal

The common faults of the hydraulic system are the hydraulic pump outer ring fault, the hydraulic pump inner ring fault, hydraulic cylinder leakage, relief valve blockage and relief valve leak. It is mainly performances in the liquid oil temperature, liquid oil pressure and relief valve flow. There are a lot of non-stationary signals in fault signals which with complexity and multilevel nature. It is difficult to extract fault features by conventional methods accurately. Therefore, in this paper, the LMD decomposition is selected to decompose fault features. And then the approximate entropy of PFs were taken to extract fault features accurately.

In the experiment, each fault was measured two groups of data respectively from the three signals which are temperature, pressure, and flow. Each group of data was decomposed by LMD and produced PFs to realize the decomposition of fault features. Then the approximate entropy of the first two PFs which from the measured data were calculated for five different faults to extract fault features. The results are shown as Table 1 - Table 5, where T is temperature, P is pressure, F is flow.

Table 1. ApEn of PFs for the hydraulic pump outer ring fault

	No.	Original signal	The first component	The second component
T	1	0.197	0.989	0.832
	2	0.898	0.976	0.805
P	1	0.235	0.312	0.152
	2	0.198	0.276	0.143
F	1	0.762	0.823	0.681
	2	0.787	0.897	0.701

Table 2. ApEn of PFs for the hydraulic pump inner ring fault

	No.	Original signal	The first component	The second component
T	1	0.652	0.729	0.608
	2	0.597	0.703	0.582
P	1	0.162	0.205	0.152
	2	0.148	0.198	0.123
F	1	0.428	0.510	0.387
	2	0.457	0.538	0.402

Table 3. ApEn of PFs for hydraulic cylinder leakage

	No.	Original signal	The first component	The second component
T	1	0.153	0.256	0.140
	2	0.169	0.270	0.142
P	1	0.102	0.204	0.096
	2	0.097	0.173	0.081
F	1	0.442	0.529	0.401
	2	0.453	0.535	0.398

Table 4. ApEn of PFs for relief valve blockage

	No.	Original signal	The first component	The second component
T	1	0.443	0.527	0.402
	2	0.457	0.561	0.421
P	1	0.887	0.976	0.805
	2	0.835	0.927	0.785
F	1	0.455	0.552	0.421
	2	0.459	0.589	0.429

Table 5. ApEn of PFs for relief valve leak

	No.	Original signal	The first component	The second component
T	1	0.532	0.629	0.497
	2	0.396	0.527	0.325
P	1	0.009	0.072	0.005
	2	0.018	0.0830	0.013
F	1	0.952	1.025	0.825
	2	0.873	0.976	0.811

3.2. Simulation analysis of experience

In the experiment, five different faults were encoded respectively as hydraulic pump outer ring fault [0 0 0 0 1], hydraulic pump inner ring fault [0 0 0 1 0], hydraulic cylinder leakage [0 0 1 0 0], relief valve blockage[0 1 0 0 0] and relief valve leak [1 0 0 0 0].

Table 6. The output results of testing samples

Testing samples	Expected output	The output of LSSVM
0.987 0.305 0.852	00001	0.002 0.001 0.002 0.003 0.998
0.832 0.153 0.681		0.001 0.012 0.004 0.002 0.987
0.726 0.198 0.538	00010	0.001 0.002 0.005 0.988 0.002
0.593 0.149 0.392		0.002 0.004 0.003 0.968 0.008
0.256 0.204 0.534	00100	0.003 0.004 0.995 0.006 0.001
0.141 0.095 0.389		0.002 0.001 0.989 0.005 0.004
0.524 0.956 0.552	01000	0.003 0.984 0.003 0.002 0.005
0.402 0.798 0.421		0.003 0.976 0.005 0.002 0.004
0.619 0.072 0.976	10000	0.997 0.002 0.005 0.004 0.001
0.497 0.013 0.826		0.985 0.001 0.003 0.006 0.004

In each fault, 50 sets of data used for training network. The number total of training samples is 250. Each group of data was decomposed by LMD and the approximate entropy of the first two PFs was calculated for training as a network input. Then 100 new samples were selected randomly for testing as LSSVM input. The output results of testing samples are shown as Table 6. Finally, Compared with EMD and wavelet decomposition which the eigenvectors were input into LS-SVM for training and testing also.

Table 7. The comparison results

Method	Training samples	Testing samples	recognition rate /%	training time /s
Wavelet -LSSVM	250	100	93.58	3.473
EMD-ApEn -LSSVM	250	100	96.97	2.902
LMD-ApEn -LSSVM	250	100	98.89	2.784

As we can see from Table 7, the fault recognition rate of LMD approximate entropy feature extraction method can reach 98.89%. Compared with EMD and wavelet decomposition, LMD approximate entropy can extract fault features more accurate. In addition, the method in this paper not only improves the fault recognition rate, but also save training time. It reached the ideal diagnostic results.

4. Conclusion

In this paper, we did research on the feature extraction and pattern recognition for mechanical fault diagnosis respectively. A feature extraction method based on LMD-approximate entropy was proposed. After LMD decomposition, calculating approximate entropy of PFs. LMD combine with approximate entropy not only can extract fault features effectively but also provides the basis for classification recognition of faults. Finally, the approximate entropy of PFs was input into LS-SVM for fault recognition. Compared with EMD and wavelet decomposition, the results show that it can extract fault features more accurate and combine it with LSSVM not only have a high fault recognition rate, but also save training time.

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