Fault Diagnosis Method of Cigarette Dust Collecting Centrifugal Fan Based on Set Empirical Mode Entropy

Wei Lv and Yu Qiao

Abstract

According to characteristics of the centrifugal fan fault signals, such as non-stationary, non-linear and sample scarcity during actual application process, a new method of ensemble empirical mode decomposition sample entropy and support vector machine fan fault diagnosis was proposed. In this method, the axial displacement signal is decomposed into a series of stable intrinsic mode functions by the EEMD algorithm firstly. Then, the phony mode components of the IMF are filtered and removed according to the correlation coefficient rule, and the entropy of the filtered IMF is calculate respectively and then be considered as the eigenvectors. Finally, the eigenvectors are put into the LIBSVM and BP neural network to carry out mode identification. At last, the feasibility, effectiveness and superiority of the above method are verified by experiments.

Key words: centrifugal fan, ensemble empirical mode decomposition, sample entropy, SVM

Introduce

Dust removal is one of the important parts of the cigarette factory production line, it is used to remove the waste tobacco, tobacco stems and other debris through the dust pipe discharge. Empirical mode decoupling (EMD) is a commonly used non-stationary, non-linear signal processing method. Compared with Fourier transform and wavelet transform, EMD can decompose non-stationary vibration signals into a series of high and low modal function components (IMF) according to different time scales. However, the IMF component has the effect of pattern

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mash up, which has a bad effect on the diagnosis result, and the overall average empirical mode decomposition (EEMD) can effectively avoid the pattern mash up by adding Gaussian white noise.

In this paper, the non-stationary signal of the centrifugal fan is decomposed by EEMD, and several IMF components are obtained, it uses the similarity coefficient criterion to calculate the similarity coefficient, to obtains the sample entropy as the eigenvector with the high similarity coefficient, it uses LIBSVM to diagnose the different states of the centrifugal fan failure and verify the feasibility of the method by experiment.

1 The decomposition step of the centrifugal fan signal EEMD

EEMD decomposition is based on the EMD, tWe use the Gaussian white noise to distribute the frequency evenly, the white noise signal is superimposed on the centrifugal fan vibration signal after several EMD decomposition, finally, we get the final decomposition result for all IMF components. The EEMD decomposition step is as follows:

1) White noise $m_n(t)$ is added to the centrifugal fan vibration signal $\zeta(t)$ several times:

$$\zeta_n(t) = \zeta(t) + m_n(t) \quad (1)$$

In the formula, where $\zeta_n(t)$ is the signal after adding the white noise for the nth time, and the effect of the EEMD modal aliasing is related to the size of the added white noise.

2) EMD decomposition of $\zeta_n(t)$, get a few IMF components($C_{nk}(t)$) and a balance($\zeta_a(t)$), where $C_{nk}(t)$ is the k-th IMF component obtained by adding the white noise to the nth time.

3) Repeat the steps 1) and 2) M times, using the principle that is random sequence of the statistical mean is 0, the corresponding IMF component of the overall average operation, the effect of Gaussian white noise on the real IMF component is eliminated, and the result of EEMD decomposition is obtained, it is:

$$c_k(t) = \frac{1}{M} \sum_{i=1}^{M} C_{nk}(t) \quad (2)$$

In the above formula, $c_k(t)$ is the k-th IMF component obtained by decomposing the centrifugal fan vibration signal EEMD. When the M value is larger, the sum of the IMF components corresponding to the white noise is
closer to zero. At this point EEMD decomposition results are as follows:

\[ \zeta(t) = \sum_{k} c_k(t) + \delta(t) \quad (3) \]

In the above formula, \( \delta(t) \) is the residual component, it represents the average trend of the final signal, it can be decomposed by EEMD any number of signals into a number of IMF components and a residual component \( (\delta(t)) \). The intrinsic modal component \( c_k(t) \) \( (k=1,2,c_1) \) represents the IMF component of the signal from high frequency to low frequency, each component is different, carrying the energy is different, and it changes with the centrifugal fan vibration signal changes. Centrifugal fan impeller quality imbalance vibration acceleration signal shown in Figure 1, the signal \( c_1 \) is decomposed by EMD to obtain nine IMF components \( ((c_2,c_3,...c_{10}))\) and one residual component \( (r(t)) \), as shown in Figure 2.

Figure 3 is the centrifugal fan of the same impeller quality imbalance vibration acceleration signal EEMD decomposition results \( (n = 100, \) the standard deviation of the standard white noise standard deviation of fivedoubles). Figure 2 shows the EMD decomposition of the original vibration signal, \( r(t) \) represents the residual component. In the Figure 2 and Figure 3, the \( c_6(t) \) are the first six modal components. In the Figure 2 and Figure 3, we can know the waveforms are not very different, in Figure 3, the amplitude of \( c_6(t) \) is small, and the degree of mash up is light, In Figure 2 and Figure 3, \( c_8(t) \) is the eighth modal component, the amplitude range of the same, But in Figure 3, \( c_8(t) \) significant change range is small, mashes are light, therefore, we conclude that the EEMD method modulates the degree of mash up with the EMD.

![Figure 1. Vibration acceleration signal of the centrifugal fan with uneven quality of impelle.](image-url)
2 The principle of algorithm for sample entropy

The sample entropy algorithm is as follows:
1) Assume that the original vibration signal is A, a total of N points;
2) A set of m-dimensional vectors are successively ordered in sequence order: from \( X_m(i) \) to \( X_m(N-m) \), thereinto, \( X_m(i) = [u(i), u(i+1), \ldots, u(i+m-1)] \) \((i=1-N-m)\), the vector represents the value of A from the i-th point;
3) Defines the distance between vectors A and B, it is \( d[X_m(j), X_m(i)] \),
\[
 d[X_m(j), X_m(i)] = \max(|u(i+k) - u(j+k)|)
\]
Thereinto, \( k = 0 \sim m-1; \quad i, j = 1 \sim N-m, j \neq i \);
4) Given the threshold \( r(r>0) \), for each \( i \leq N-m \) value, statistical \( d[X_m(i), X_m(j)] \) is less than the number of \( r \), (template match number) and the ratio of this number to the distance number of \( N-m-1 \), as \( B^m_r(i) = N^m(i) / (N-m-1) \), find its average for all \( i \), it is
\[
 B^m_r(r) = (N-m)^{-1} \sum_{i=1}^{N-m} B^m_r(i);
\]
5) Increase the dimension \( m+1 \), constitute a set of \( m+1 \) dimensional vector, repeat steps 2), 3) and 4), we get:
\[
\begin{align*}
 B^{m+1}_r(r) &= (N-m)^{-1} \sum_{i=1}^{N-m} B^{m+1}_r(i) \\
 SampEn(m, r, N) &= -\ln[ B^{m+1}_r(r) / B^m_r(r)]
\end{align*}
\]
Obviously, $SampEn(m,r,N)$ is related to the parameters $m$, $r$ and $N$, under normal circumstances $m = 2$ or $1, r = 0.1 \sim 0.25\delta, \delta$ is the standard deviation of the data). The sample entropy of the centrifugal fan vibration signal has good statistical properties. The complexity of measuring the vibration signal of centrifugal fan with sample entropy is mainly as follows: the value of the sample entropy is large, which indicates that the centrifugal fan vibration signal has a high degree of complexity, the sample entropy is small, indicating that the signal sequence similarity is high.

3 Principle of SVM

The main idea of the support vector machine is to establish a classification hyperplane as a decision plane, so that the isolation edge between the positive and the counter-examples is maximized to achieve sample classification. The specific form of the support vector machine model is as follows:

1) Assume the known sample training set

$$T = \{(x_i, y_i), \ldots, (x_l, y_l)\} \in (X \times Y)^l \quad (5)$$

among them, $x_i \in X = \mathbb{R}^n$, $y_i \in Y = \{1, -1\} (i = 1, 2, \ldots l)$, $x_i$ is the eigenvector.

2) Select the appropriate kernel function and parameter $C$ construction problem model and find the optimal solution, as follow:

$$\min_{a} \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} y_i y_j a_i a_j K(x_i, x_j) - \sum_{j=1}^{l} a_j \quad (6)$$

$$\sum_{i=1}^{l} y_i a_i = 0, \ 0 \leq a_i \leq C, \ i = 1, \ldots, l$$

Get the optimal solution: $a^* = (a_1^*, \ldots, a_l^*)^T$.

3) Select a positive component $0 < a_i^* < C$ of $a^*$ and calculate the threshold:

$$b^* = y_i - \sum_{i=1}^{l} y_i a_i^* K(x_i, x_i) \quad (7)$$

4) Constructing a sample decision function

$$f(x) = \text{sgn} \left( \sum_{i=1}^{l} a_i^* y_i K(x_i, x_i) + b^* \right) \quad (8)$$

At first, a support vector machine was designed to solve the problem of two classifications. When faced with many kinds of problems, we need to design and construct multi-valued classifier. Now, the design of SVM classifier method is divided into two categories:
① indirect method, mainly by a number of two classifier combination;
② direct method, directly modify the objective function entropy, will solve the parameters of multiple classifiers into an optimization problem, by seeking the optimization problem "one time" solution, to achieve multi-value classification. In this paper, by the Taiwan University Lin Zhiren and other development LIBSVM toolbox combined with centrifugal fan shaft is not right, bearing failure, quality imbalance, mechanical rubbing, normal operation and other 5 cases, using indirect method, design 10 SVM, the centrifugal fan vibration signal identification.

4 Experimental system and method

In the experimental system, the dust centrifugal fan model is 2BH1400-7AH16 high pressure fan, the maximum speed of 2900r / min, wind pressure 803Pa, air volume of 1830m3 / h. The position and overall structure of the centrifugal fan experiment system are shown in Fig.4. A bracket is fixed in the vertical and horizontal directions of the fan shaft, and a displacement sensor is mounted on the bracket to measure the radial displacement, install another displacement sensor on the vertical plane of the coupling on the side of the centrifugal fan to measure the axial displacement; install the acceleration sensor vertically on the bearing seat to measure the acceleration signal. The following four kinds of faults are constructed for the centrifugal fan vibration signal:
1) Mechanical rubbing, by the friction frame loaded on the centrifugal fan to produce rubbing to achieve.
2) Bearing failure, load the fault bearing on the centrifugal fan to achieve bearing failure
3) The rotor is misaligned and the motor and the centrifugal fan shaft are misaligned by moving the motor
4) Quality imbalance, the metal block welded in the fan wheel rear panel, resulting in centrifugal fan impeller quality imbalance failure

5 Experimental results and analysis

The EEMD is used to decompose the vibration signals of the above five kinds of centrifugal fans. The average number of operations is 100, and the standard deviation of white noise and vibration signal is 0.1, centrifugal fan
rotor misaligned EEMD signal shown in Fig.5. In the case of fan rotor misalignment, \( c_1 \) is the original signal, EEMD decomposition results are 8 IMF components (\( c_2, c_3, \cdots, c_9 \)) and 1 residual component (\( \delta \)), the time scale of the component is from small to large, and the spectrum is distributed from high frequency to low frequency.

Using EEMD to Decompose Vibration Signal of Centrifugal Fan, due to the action of the EEMD algorithm and the interference of the noise signal, there will be an over-decomposition phenomenon, resulting in a false pattern, showing a number of irrelevant IMF components. These components can not represent the characteristics of the original signal, will also affect the results, the correlation coefficient between the IMF component and the fault signal is calculated by using the cross correlation criterion. It is found that the correlation between the first five IMF components and the original signal is large, and the correlation between the other IMF components and the fault signal is in the order of 0.001 or less. These components as the real weight, the sample entropy is calculated to realize the feature extraction of the fault signal. The sample entropy of the centrifugal fan under different working conditions is shown in Fig. 6.

![Image](image.png)

Figure 5. The EEMD signal of centrifugal fan rotor misalignment.
Figure 6. Sample entropy of the centrifugal fan under different conditions.

The final state of each group were taken 80 groups, a total of 400 fault samples for centrifugal fan failure pattern recognition. And 60 randomly selected as the training samples, 30 groups as the test samples, respectively, into the LIBSVM and BP neural network (BPNN), the test results in Tab.1. In order to compare the recognition effect of LIBSVM and BPNN, the training and testing of LIBSVM and BPNN were carried out in 50 and 60 training samples. As can be seen from Tab.1: when the training sample is 50, the correct rate of LIBSVM recognition is significantly higher than BPNN; BPNN increases with the number of training samples, but the recognition accuracy is still higher than that of LIBSVM. Obviously, if BPNN is used for fault identification, a large number of samples are required for training. But the actual application process, training samples (collection of available fault characteristics of the signal) is relatively lacking. In summary, LIBSVM is more suitable for practical fault diagnosis and condition monitoring.
Table 1. Comparison of the experimental results.

<table>
<thead>
<tr>
<th>classifier</th>
<th>fault type</th>
<th>the rotor is not right</th>
<th>impeller quality imbalance</th>
<th>mechanical rubbing</th>
<th>normal operation</th>
<th>bearing damage</th>
<th>correct rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>BPNN(50)</td>
<td>78.7%(118/150)</td>
<td>25</td>
<td>18</td>
<td>23</td>
<td>28</td>
<td>24</td>
<td></td>
</tr>
<tr>
<td>BPNN(60)</td>
<td>83.4%(125/150)</td>
<td>27</td>
<td>21</td>
<td>27</td>
<td>26</td>
<td>24</td>
<td></td>
</tr>
<tr>
<td>LIBSVM(50)</td>
<td>92.0%(138/150)</td>
<td>28</td>
<td>24</td>
<td>28</td>
<td>29</td>
<td>29</td>
<td></td>
</tr>
</tbody>
</table>

6 Conclusions

1) EEMD method modal mashup degree than the EMD decomposition degree of mixing, screening out the sample entropy characteristics can be more correct to show the centrifugal fan state changes.

2) EEMD is suitable for dealing with the non-linear, non-stationary signal of centrifugal fan vibration. The IMF component obtained by EEMD highlights the different local feature information of the original signal, which is helpful for feature extraction.

3) Compared with BP neural network, LIBSVM is more suitable for small sample recognition, and has wide application prospect.

7 References


