Fault Diagnosis of Motor Based on VMD-Sample Entropy-Random Forest

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Abstract. Traditional fault diagnosis of DC motors methods need to establish accurate mathematical models, effective state estimations, estimation of parameters and appropriate statistical decision-making methods. These preconditions make the traditional motor fault diagnosis have considerable limitations. To address this issue, a new mechanical fault diagnosis method is proposed. Firstly, the vibration signals of rotary bearing are collected by the designed acquisition system. Then, the variational mode decomposition (VMD) is adopted to decompose the signal into a series of intrinsic mode function, and the characteristics of the vibration signal are extracted by sample entropy. Finally, random forest uniting SPRINT algorithm is used to identify vibration signals of rotating machinery, which each branch tree is trained by applying different bootstrap sample sets. The results have shown that the proposed fault diagnosis method has good generalization performance and the recognition rate samples is more than 90%. Compared with traditional neural network, and it has no use for carrying out the verbose process of parameter optimization.

1. Introduction

DC Motors play a crucial role in factory reliability. It has huge impact not only on personal safety, but also efficiency of operations[1]. Therefore, it is important to study the fault diagnosis of the motors, so as to maintain the motor in time and minimize economic damage. During the past several decades, lots of DC Motors fault diagnosis studies were about the mechanical vibration signals[2–3] and all these studies could be successfully employed to a certain extent since the vibration signals generated by mechanical components often provide variety of dynamic information about mechanical system situation.

The main contribution of this paper is to propose a novel mechanical fault diagnosis method for DC motor based on VMD, SampEn and the optimal RF, where the optimal RF classifier is established by using the SPRINT method of decision tree. Firstly, the signal acquisition system is designed in LabVIEW 2014, and the translation invariant of wavelet de-noising is utilized to de-noise the signals. Then, after extracting the physically meaningful modes by the VMD algorithm, and the signal features are calculated by the SampEn method. Finally, the improved RF classifier is employed to identify the label samples.

2. Variational Mode Decomposition (VMD)

VMD algorithm decomposes the adaptive quasi-orthogonal signal f into discrete quasi-orthogonal band-limited signal $N_k$ with certain sparsity. Each mode revolves around the center frequency $\omega_j$. VMD uses Wiener filter to remove the drying which has a good effect. The estimated K central angular frequencies
are obtained by setting the finite broadband parameter (a) and the central angular frequency initialization method. The modal functions $U_k$ are obtained according to different central angular frequencies B. Each modal function is a single component AM-FM function[4-5]:

$$U_k = A_k(t) \cos[\phi(t)].$$  

(1)

In the formula, the phase function $\phi(t)$ is a monotone nondecreasing function, therefore the instantaneous angular frequency $\phi'(t) > 0$. The envelope $A_k(t) > 0$, and the change rate of $\omega(t) = \phi'(t)$ is much faster than that of $A_k(t)$ and $\phi(t)$. The process of VMD can be considered as the construction and solution of a constrained variational problem described by Equations (2)

$$\min \left\{ u_k, \omega_k \right\} \left\{ \sum_{k=1}^{K} \left\| \partial_t \left( \sigma(t) + \frac{j}{\pi t} \right) u_k(t) e^{-j\omega_k t} \right\|^2 \right\}$$  

(2)

Here, in the equations $u_k$ is the sub-signals and $\omega_k$ is the center frequencies of the sub-modes. $\partial_t$ is the partial derivative of the function to find time $t$; $\sigma(t)$ is the unit pulse function; $j$ is the imaginary unit; * is the convolution. In order to render the problem unconstrained, the quadratic penalty term and Lagrangian multipliers are brought, and the problem is rewritten as Equation (3).

$$L(u_k, \omega, \lambda) = \alpha \sum_{k=1}^{K} \left\| \left( \sigma(t) + \frac{j}{\pi t} \right) u_k(t) e^{-j\omega_k t} \right\|^2 \left( \lambda(t), f(t) \sum_{k=1}^{K} u_k(t) \right)$$  

(3)

$\alpha$ is penalty term(also called Equilibrium constraint parameter), $\lambda$ is Lagrange multiplicator. The saddle point is found by using the alternate direction method of multipliers (ADMM)[6].

3. Sample Entropy

In general, as for time series are composed of N data \{x(n)\} = x(1), x(2), \rightarrow, x(t), the sample entropy is calculated as follows[7-8]:

1. A sequence of vectors of dimension m, $X_m(1) \rightarrow X_m(N - m - 1)$, where $X_m(i) = \{X(1), X(2), \rightarrow X(i) \rightarrow X(i + m - 1)\}, 1 \leq i \leq N - m + 1$. These vectors represent the value of M continuous x, where it starts from the i-th point.

2. The distance $d[X_m(i), X_m(j)]$ between vector $X_m(i)$ and $X_m(j)$ is defined as the absolute value of the maximum difference between the two corresponding elements

$$d[X_m(i), X_m(j)] = \max_{k=0, \ldots, m-1} \{|x(i + k) - x(j + k)|\}$$

3. As for $X_m(i)$, the number of j (1 \leq j \leq N - m, j \neq i) whose distance between $X_m(i)$ and $X_m(j)$ is less than or equal to r is counted and denoted Bi. For 1 \leq i \leq N - m, there is:

$$B_i^m = \frac{1}{N-m} * B_i$$

(4)

4. Define $B^{(m)}(r)$ as

$$B^{(m)}(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} B_i^{(m)}(r)$$

(5)

5. Increasing the dimension to m+1, the number of distances between $X_{m+1}(j)$ and $X_{m+1}(j)$ (1 < j < N - m, j \neq i) that is less than or equal to r is calculated and denoted as $A_i$. $A_i^{(m)}(r)$ is defined as:

$$A_i^{(m)}(r) = \frac{1}{N-m-1} A_i$$

(6)

6. Define $A^m(r)$ as

$$A^m(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} A_i^m(r)$$

(7)
Thus, \( B^m(r) \) is the probability of two sequences to match \( m \) points under similar tolerance \( r \), while \( A^m(r) \) is the probability of two sequences matching \( m+1 \) points. Sample entropy is defined

\[
\text{SampEn}(m, r) = \lim_{N \to \infty} \left\{ -\ln \left( \frac{A^m(r)}{B^m(r)} \right) \right\}
\]

When \( N \) is a finite value, it has been serimated following Equations:

\[
\text{SampEn} = -\ln \left( \frac{A^m(r)}{B^m(r)} \right)
\]

4. Random Forest

RF is an algorithm based on classification tree. The traditional machine learning model is neural network, which can predict accurately. However the learning speed of neural network is slow, and the simple problems need to train hundreds of thousands times and easily fall into local minimum. Compared with the neural network, random forest can effectively balance the error when there is imbalance in classification, and it is fast network-training speed. Based on the above statements, a RF approach is proposed with SPRINT in this paper. It is similar to bagging algorithm. It is based on Bootstrap method to resample and generate multiple training sets. It is difference that it is proposed a method that a split attribute set is randomly selected. When reconstructing decision tree, the detailed random forest algorithm flow is shown below: Bootstrap method is used to resample and generate \( T \) training sets randomly \( S_1, S_2, S_3 \rightarrow S_T \). Each training set is employed to generate the corresponding decision tree \( C_1, C_2, C_3 \rightarrow C_T \). Before selecting attributes on each non-leaf node (internal node), \( m \) attributes are randomly extracted from \( M \) attributes as the split attributes set of the current node, and the node is split by the best split method of the \( m \) attributes. Every tree grows intact without pruning. As for the test set sample \( X \), it gets the corresponding category by testing each decision number[9].

5. Experimental Results and Analysis

In this paper, 50 samples per each mechanical state are collected by acquisition system. Figure 1 shows the time domain waveform of Normal signal and three types of fault signals, the sampling frequency is 10 KS/s, and the sampling time is 0.7. Here are 7 components that have been decomposed from measured signals in figure 1.
Figure 1 Vibration Components of signals obtained by VMD method. 
(A) Normal; (B) Fault I; (C) Fault II; (D) Fault III

Figure 2 Performance Analysis of Forests Classifier
There are many classifiers (decision tree) in random forest. The parameters of each classifier are different, and the training sample sets of each classifier are different. Therefore, different classifiers will be generated to make the diagnosis results of each classifier inconsistent. Finally, the final classification results are generated by voting. It will effectively improve the accuracy of diagnosis. From the figure below, we can see the recognition rates of four conditions. Blue circles represent the correct recognition samples, and red stars represent the wrong recognition samples. It can be seen from the results, there are
80 samples set in the testing set, the normal state is not misidentified, and there is one sample recognition error in the other three faults. The vibration signal recognition rate are: Normal 100%, Fault I 95%, Fault II 90%, Fault III 90%. In this paper, the effect of random forest generalization is discussed. Figure 17 shows that the abscissa represents all decision tree (500 trees) of random forest, and the training set samples; the ordinate represents the test set samples, and the abscissa and longitudinal coordinates satisfy X+Y=500.

Table 1 Final Recognition Results

| Parameters          | Normal | Fault I | Fault II | Fault III | All Test |
|---------------------|--------|---------|----------|-----------|----------|
| LQV                 |        |         |          |           |          |
| Hidden Layer=6;     | 70%    | 70%     | 85%      | 85%       | 77.5%    |
| Hidden Layer=25;    | 80%    | 85%     | 85%      | 90%       | 85%      |
| Hidden Layer=46     | 85%    | 90%     | 80%      | 85%       | 85%      |
| ELM                 |        |         |          |           |          |
| Activation Function (Sin); | 75%    | 80%     | 80%      | 90%       | 81.25%   |
| Activation Function (Sig); | 90%    | 80%     | 80%      | 85%       | 83.75%   |
| Activation Function (Hardlim); | 75%    | 80%     | 80%      | 90%       | 81.25%   |
| Random Forest       |        |         |          |           |          |
| Decision Tree (200); | 100%   | 85%     | 90%      | 85%       | 90%      |
| Decision Tree (500); | 100%   | 95%     | 90%      | 90%       | 93.75%   |
| Decision Tree (900); | 95%    | 80%     | 85%      | 90%       | 87.5%    |

The parameters of decision tree are list above table. Besides, the final recognition results of these three classifiers are shown in Table 6. It had shown different parameters recognition rate in the table. From the table, It has seen the best parameters for each method. It also shows that samples of Fault II and Fault III recognition rate is lower than other states by using each fault diagnosis method, while the samples of Fault II and Fault III are easily misidentified, these indicate that the vibration signals of the fault I condition are very different from the vibration signals of the other three conditions. Compared optimal random forest classifier with LQV, ELM and decision tree classifiers, It shows that using the same feature extraction method, Decision tree method is better than other two neural network, the recognition rates of improved RF classifier are higher than other methods.

6. Conclusions

This paper presents a new method for mechanical fault diagnosis of DC motor. Firstly, the original vibration signals are collected by designed acquisition system which is designed by Labview2014, and secondly, VMD is employed to decompose the vibration signals into a series of physically meaningful modes, and then, sampEn method is used for feature extraction. Finally, random forest method is employed to identify four mechanical conditions, the simulation and practical test results demonstrate the following advantages of the new method: Compared with EMD, methods, the VMD method can better decompose the signals into a series of physically meaningful modes, while the VMD method can solve the mode aliasing well. According to the final recognition rates, the VMD-SampEn feature extraction method and the optimal RF classifier are more suitable for mechanical fault diagnosis of DC motors, the signal features obtained by VMD-SampEn method are more significant. The proposed RF method provides a new idea for mechanical feature extraction of DC motors.

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