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Support Vector Machine Bearing Fault Diagnosis Based On Contrast Multi-kernel Parameter Modulation

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Abstract:- In view of the limitations of SVM in processing data and classification, a bearing fault diagnosis method based on LMD support vector machine is proposed. The parameter tuning of kernel function directly affects bearing fault diagnosis efficiency. Seven kernel functions are selected for parameter tuning evaluation in this paper.In this paper, the signal is decomposed into a series of PF components by the local decomposition algorithm, and six components are selected to form the eigenvector. Secondly, the experimental data were randomly extracted and combined as a training set and a test set to test the prediction accuracy of seven kernel functions under different penalty parameters. Finally, seven kernel functions are evaluated by Frideman test, and the radial basis kernel function have the best performance.

Keywords:- *Support Vector Machine;Local Mean Decomposition;kernel function;Bearing fault diagnosis.*

I. INTRODCUTION

Rotating machinery refers to machinery that mainly relies on rotating action to complete specific functions. If it fails, it will affect the operation of related equipment of the entire production line. Therefore, fault diagnosis of rotating machinery is the key to ensure its normal work, while traditional fault detection cannot meet the detection requirements to a large extent. In the bearing fault diagnosis, the signal containing fault information should be accurately extracted and the fault information should be extracted. In this paper, LMD support vector machine bearing fault diagnosis method is used to decompose the signal into a series of positive and continuous PF components with physical significance, and the advantages of no negative frequency, under enveloping and enveloping phenomenon are combined with the advantages of support vector machine robustness on small sample data, and different kernel functions are adjusted and their performance is compared. The accuracy and efficiency of bearing fault diagnosis are improved.

II. LMD ALGORITHM AND ENERGY FEATURE EXTRACTION

There are a large number of non-stationary signals in rotating mechanical signals with high dimensions, which are not suitable for being directly used as feature inputs for machine learning. Therefore, it is necessary to process signals and extract information such as their feature values to reduce the input feature dimensions. Local mean decomposition (LMD) method, which has a fast operation speed, can decompose a complex non-stationary signal into a series of positive and continuous PF components with physical significance, and this algorithm can better solve the phenomena of negative frequency, under envelope and envelope in EMD algorithm [1.].Therefore, this paper will use LMD algorithm to process the bearing vibration signal.

A. LMD algorithm

The LMD algorithm is as follows[2.] : Obtain the original signal $x(t)$ from the sensor, find out the local extreme point n_i, and use the following formula:

$$\begin{cases} m_i = \dfrac{n_i + n_{i+1}}{2} \\ a_i = \dfrac{|n_i - n_{i+1}|}{2} \end{cases} \tag{1}$$

A local average m_i and local envelope value a_i, in t_{ni} and t_{ni+1} times respectively m_i and a_i straight line extension, by using the method of moving average smoothing, respectively to get the local mean value function $m_{11}(t)$ and local envelope function $a_{11}(t)$;subtract $m_{11}(t)$ from $x(t)$ to get $h_{11}(t)$,demodulate $h_{11}(t)$ with $a_{11}(t)$,and get $s_{11}(t)$,which is

$$s_{11}(t) = \frac{h_{11}(t)}{a_{11}(t)} \tag{2}$$

At this time, it is necessary to determine whether $s_{11}(t)$ is a pure frequency modulation function, that is, whether the conditions are met: $s_{11}(t)$ margin of envelope size is 1, if it does not meet the conditions, with $s_{11}(t)$ as a new original signal, the iterative process above, until they get a pure frequency modulation signal $s_{1n}(t)$, and the whole iterative process of local envelope function multiplication, get the envelope signal $a_1(t)$, and pure frequency modulation signal multiplication, The first PF component of the original signal is obtained, a new signal $u_1(t)$ is obtained by subtracting the $PF1$ component from the original signal $x(t)$, and the process is repeated until $u_k(t)$ is a monotone function. After many iterative decomposition cycles, $x(t)$ can be expressed as:

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$$x(t) = \sum_{p=1}^{k} PF_p(t) + u_k(t) \quad (3)$$

B. Extraction of PF energy features

To extract PF energy features, firstly, the energy E_i of each PF_i needs to be solved, that is:

$$E_i = \int_{-\infty}^{+\infty} |PF_i(t)|^2 dt \quad i = 1, 2, 3, ..., N \quad (4)$$

Then take E_i as the element of the eigenvector:

$$T = [E_1, E_2, E_3, \cdots, E_N] \quad (5)$$

Finally, it is normalized as follows:

$$\begin{cases} E = \left(\sum_{i=1}^{N} |E_i|^2 \right)^{1/2} \\ T_0 = \left[\frac{E_1}{E}, \frac{E_2}{E}, \frac{E_3}{E}, \ldots, \frac{E_N}{E} \right] \end{cases} \quad (6)$$

III. SUPPORT VECTOR MACHINE

A. Support vector machine theory foundation

Support vector machine is widely used in pattern recognition and other fields, its main idea is to find a hyperplane, the maximum separation of two types of data, low complexity, global optimal, good robustness and other advantages.

Suppose that the training sample set consists of two classes denoted as $y_i = 1$ and $y_i = -1$ .If there is a classification hyperplane, the sample can be divided into two classes:

$$\omega^T \cdot x + b = 0 \quad (7)$$

Where: ω is the norm of the hyperplane;b indicates the classification threshold. The distance d between the hyperplane and the support vector machine is $\frac{1}{\|\omega\|}$, and the solution maximization distance is $\frac{1}{2}\|\omega\|^2$ converted to solution minimization, so the basic model of the support vector machine[3.] is

$$\begin{cases} \min_{\omega, b} = \frac{1}{2} \|\omega\|^2 \\ s.t.\ y_i(\omega^T x_i + b) \geqslant 1 \quad i = 1, 2, 3, ..., m \end{cases} \quad (8)$$

B. Selection of seven kernel functions

Kernel function is an efficient tool to map low-latitude data to high-latitude features. It not only helps us to deal with partial linear indivisible problems, but also keeps the computational time complexity in low dimension, so the computational efficiency is very high. Kernel function selection and kernel parameter optimization are always difficult problems in support vector machine algorithm. For rotating machine bearing fault diagnosis, we should take into account the accuracy of diagnosis and the convenience of parameter selection to select and optimize the kernel parameters.

Aiming at the parameter tuning problem of different kernel functions in support vector machine, this paper selects 7 kernel functions for parameter tuning evaluation, 7 kernel functions are shown in Table 1.There are four one-parameter kernel functions, one half-parameter kernel functions and two no-parameter kernel functions. The four single parameter kernel functions are Gaussian kernel function, exponential radial basis kernel function, Cauchy kernel function and Hermite kernel function[4.].Semi-parametric kernel function is trigonometric modified Legendre kernel function[5.], which is called semi-parametric kernel function because its parameters are only parameterized in natural numbers, which can greatly simplify kernel optimization. The kernel-free functions we choose are sinusoidal trigonometric kernel-free functions and dimensionally combined kernel-free functions. Both types of kernel functions come from New empirical nonparametric kernels for support vector machine classification[6.],These two kernel functions are named new non-linear kernels and application specific kernel in this article. In this paper, for the convenience of discussion, we named it trimodif kernel and new empirical non-parametric kernel function respectively.

Table 1: Seven kernel functions

Parameter number	Kernel function	Expression
Single parameter	Gaussian kernel	$K(x,y)=\exp\left(-\frac{\|x-y\|^2}{2\sigma^2}\right)$
	Radial Basis kernel	$K(x,y)=\exp\left(-\frac{\|x-y\|}{2\sigma^2}\right)$
	Cauchy kernel	$K(x,y)=\frac{1}{1+\frac{\|x-y\|^2}{\sigma}}$
	Hermite kernel	$K(x,y)=\left(1-\frac{\|x-y\|}{\lambda}\right)\sum_{i=0}^{n}p_i(x)p_i^T(y)$ $p_0(x)=1$ $p_1(x)=x$ $p_n(x)=\frac{2n-1}{2}p_{n-i}^T(x)-\frac{n-1}{n}p_{n-2}(x)$
Half parameter	Legendre kernel	$K(x,y)=\frac{1}{(1-q^2)^{\frac{m}{2}}}\exp\left(\frac{2q\|x-y\|}{1+q}-\frac{\|x-y\|}{1-q^2}\right)$
Parameter-free	Trimodif kernel	$K(x,y)=1-\sin\left(\frac{\pi\|x-y\|}{z}\right)$ $z=\max(\|x_i-y_i\|)$
	New empirical non-parametric kernel	$K(x,y)=1-\left(1+\sum_{i=1}^{3}\frac{(-1)^i}{\left(\frac{\|x-y\|}{z}\right)^i+1}\right)$ $z=\max(\|x_i-y_i\|)$

C. Bearing fault diagnosis based on LMD SVM method

The flow chart of SVM method based on LMD is shown in Figure 1.

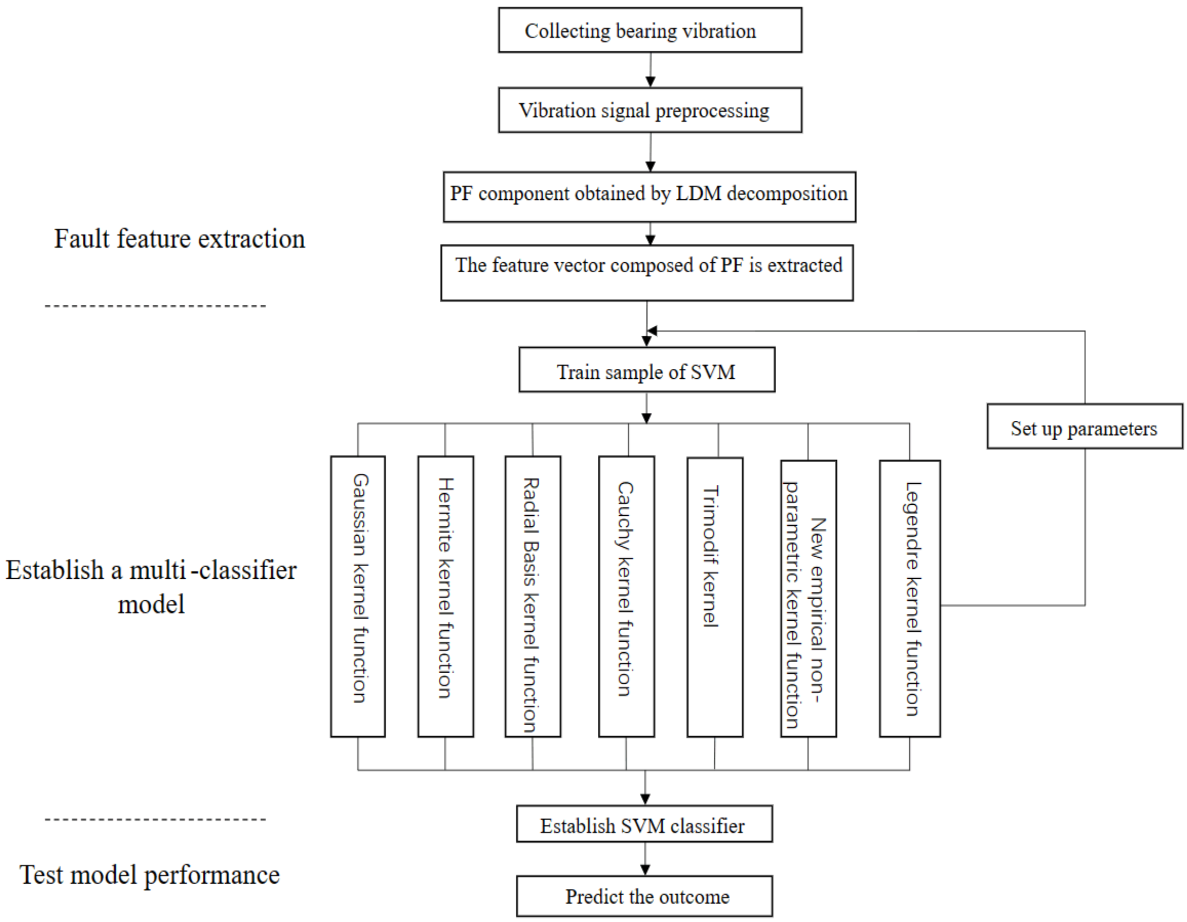

Fig. 1: Flow chart of bearing fault detection based on LMD SVM method

IV. EXPERIMENTAL PROCESS

A. Experimental data

Based on the bearing fault data of DC competition, bearing fault is divided into four modes: normal, outer ring fault, inner ring fault and ball fault. 500 pieces of data are taken from each of the four modes to form four groups of data with the same proportion. The training set and test set of each experiment were randomly selected from each type of mode according to 7:3 training test ratio.

LMD algorithm was used to decompose each group of data into several PF components. In this paper, six PF components PF1-PF6 were selected to extract their energy eigenvalues and form energy eigenvectors, which were classified by SVM algorithm. The normalized energy characteristics of the four bearing fault modes are shown in Table 2.

Table 2: Normalized energy characteristics under four bearing failure modes

Fault type	E_1	E_2	E_3	E_4	E_5	E_6
Normal	0.4722	0.1514	0.2500	0.0920	0.0215	0.0126
Ball	0.9713	0.0179	0.0064	0.0038	0.0002	0.0001
Inner	0.8002	0.1166	0.0701	0.0100	0.0022	0.0007
Outer	0.9583	0.0330	0.0061	0.0017	0.0003	0.0002

B. Kernel function parameters

In this experiment, the classifier is trained by training set to obtain the optimal classification model, and then the classification model is tested by test set. Each kernel function is randomly tested 5 times. The penalty parameter C in SVM takes three values of 10, 100 and 1000 respectively. Under the penalty parameter C takes these three values, the classification accuracy level represents the kernel function performance index. This article specifies that the parameters of each kernel function traverse 9 values, and the parameters range is shown in Table 3:

Table 3: Kernel parameter range

Kernel function	**Argument**	**Value range**
Gaussian kernel function	σ	2^{-4}~2^{4}
Radial Basis kernel function	σ	2^{-4}~2^{4}
Cauchy kernel function	σ	2^{-4}~2^{4}
Hermite kernel function	n	1~9
Legendre kernel function	q	0.1~0.9

Table 4 shows the model training prediction accuracy and corresponding optimal parameters of 7 kernel functions with 3 different values of penalty parameter C.

Table 4: SVM model training results

Penalty parameter	Kernel function	Gaussian kernel	Radial Basis kernel	Cauchy kernel	Hermite kernel	Legendre kernel	Trimodif kernel	New empirical non-parametric kernel
10	Accuracy rate (%)	74.40 ±2.26	91.73 ±2.93	82.93 ±4.40	87.73 ±2.93	93.86 ±2.14	81.59 ±3.07	85.73 ±2.14
	Optimal range	16	8	0.625	0.9	2,4	None	None
100	Accuracy rate (%)	84.53 ±2.80	92.67±1.33	85.06 ±4.27	90.93 ±1.73	93.06 ±2.27	82.66 ±2.67	93.29 ±2.13
	Optimal range	16	2，4	0.125 0.425 0.625	0.9	2，4	None	None
1000	Accuracy rate (%)	87.46 ±3.20	93.06±1.60	86.53 ±3.47	92.73 ±1.27	92.93 ±1.73	82.40 ±2.93	94.54 ±2.13
	Optimal range	16	0.5 1 4	0.25 0.625	0.9	2，4	None	None

C. Comparison of tuning performance of seven kernel functions

According to the training results in Table 4, Frideman test was conducted to obtain the performance scores of seven kernel functions under the penalty parameter C, and the score comparison results are shown in Table 5.

Table 5: Kernel function performance comparison

	C=10	**C=100**	**C=1000**
	mark	**mark**	**mark**
Gaussian kernel	1	1.9	3
Hermite kernel	5	4.3	4.9
Legendre kernel	6.7	5.8	5.4
Radial Basis kernel	6.1	6.1	5.3
Cauchy kernel	2.7	2.3	2.2
Trimodif kernel	2.5	1.8	1.1
New empirical non-parametric kernel	4	5.8	6.1

Rank Frideman test results on average, as shown in Figure 2 below:

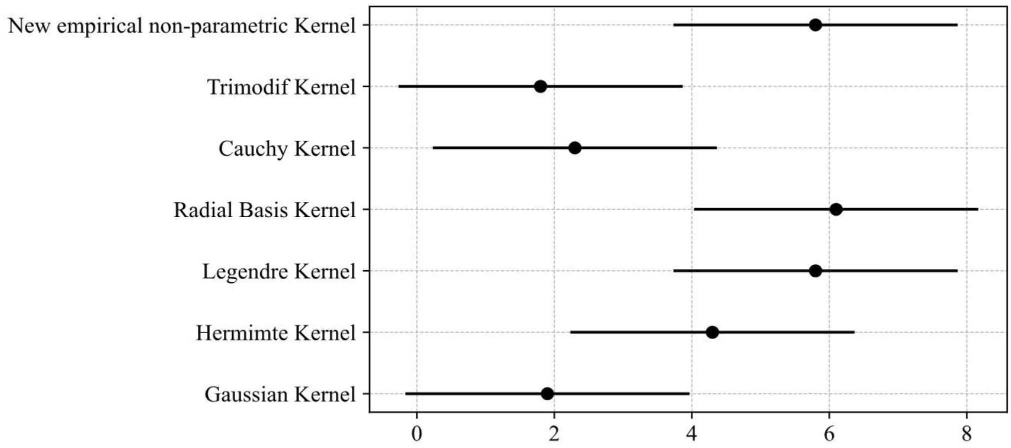

Fig. 2: Kernel function performance sorting

As can be seen from Figure. 2, exponential radial basis kernel function and legendre kernel function have better performance than Gaussian kernel function, and trimodif kernel function and Cauchy kernel function have similar performance to Gaussian kernel function. The radial basis kernel function has the best performance and can be used for bearing fault detection of LMD support vector machine.

V. CONCLUSION

By comparing seven kernel functions for parameter tuning optimization, LMD support vector machine algorithm has the following advantages for bearing fault diagnosis:

- Using LMD algorithm to extract energy characteristics from bearing fault data, a series of PF components can be accurately obtained without negative frequency, underenvelope and envelope phenomenon;
- SVM algorithm based on trigonometric modified kernel function has the characteristics of simple structure, classification accuracy and high robustness;
- By comparing 7 kernel functions and conducting parameter tuning optimization, it is concluded that the LMD support vector machine algorithm based on triangular modified kernel function has good effect on bearing fault detection and is a new fault detection method.

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