Sensor Fault Diagnosis Based on Ensemble Empirical Mode Decomposition and Optimized Least Squares Support Vector Machine

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***Abstract*—A fault diagnosis method for sensor fault based on ensemble empirical mode decomposition (EEMD) energy entropy and optimized structural parameters least squares support vector machine (LSSVM) is put forward in this paper. Firstly, the original output fault signals are pretreatment with EEMD, and then the EEMD energy entropy is extracted as the fault feature vector. Then the radial basis function (RBF) kernel function parameters and the regularization parameter of LSSVM are optimized by using chaotic particle swarm optimization (CPSO) algorithm. Finally, with the applying of proposed diagnosis method, the model of sensor fault diagnosis is built for identification and decision. The diagnostic results show that the proposed method can identify sensor fault effectively and accurately.**

***Index Terms*—Fault diagnosis, EEMD energy entropy, LSSVM, CPSO, Pressure sensor**

I. Introduction

Sensor, as the source of data acquisition, plays a vital role in automatic and intelligent system. The operation of system, the accuracy of analysis and the correctness of decision directly depend on the measurement results. Especially in the manufacturing industry, aerospace industry and rail transport, unbearable consequences would happen once the sensor fault occurs. Thus it's necessary to research on the sensor fault detection and diagnosis [1]. When the senor fault occurs, several fault features forms of output signals are exposed frequently: bias, spike, periodic interference, noise, drift and stuck. However, the fault signals are unstable and the frequency components are complex, it's difficult to conduct time-domain analysis or frequency-domain analysis individually to obtain the fault feature correctly. In reference [2], in order to diagnose the different kinds of sensor faults, a wavelet and wavelet packet transform (WPT) is introduced to the output signals, and the energy gradients are calculated in different scales. In reference [3], multiple sensor fault detection, isolation and accommodation method based on neural network is presented in UAV simulation, but the RBF neural network can easily fall into the local optimum. In reference [4], a wireless sensor fault diagnosis method is presented based on CPSO and SVM, the diagnostic results show that the CPSO-SVM has higher diagnostic accuracy of wireless sensor than PSO-SVM and BP neural network.

In order to solve mode mixing problem, EEMD is introduced, which IMFs can be extracted from an unstable signal. Signal energy in different frequency band changes when sensor fails, thus a fault diagnosis method is put forward based on the EEMD energy entropy and optimized LSSVM. In order to show the superiority of LSSVM in nonlinear and high dimension pattern recognition, other methods are presented compared to the method proposed in this paper.

II. EEMD Method

A. Ensemble Empirical Mode Decomposition

EEMD is an adaptive signal decomposition method and shows a good signal to noise ratio, which can be appropriate for the analyzing nonlinear and nonstable process, overcomes the mode mixing effect [5-6]. EEMD take advantage of Gauss white noise, which is a uniform distribution in frequency domain. When adding the white noise, signal becomes continuous in different scales, in which way to reduce the mood mixing. The principles and decomposition steps are as follows [7-9]:

(1) Add a random Gaussian white noise $n(i)$ with magnitude α to the original time series $x(i)$, and generate a new signal.

$$y(i) = x(i) + \alpha n(i) \qquad (1)$$

(2) Decompose the signal which has been processed with EMD according to (2), and gain several IMFs.

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$$y(i)=\sum_{S=1}^{S}c_s(i)+r_s(i) \tag{2}$$

Where S is the number of IMFs, $r_s(i)$ is the final residue, and $c_s(i)$ is the IMFs $(c_1, c_2, ...c_S)$.

(3) Repeat Step (1) and Step (2), and change the amplitude of white noise for each time.

(4) Calculate the ensemble average of IMFs as the final results.

$$c_s(i)=\frac{1}{A}\sum_{a=1}^{A}c_s^a(i) \tag{3}$$

B. Energy Entropy of EEMD

Generally, IMFs which are gained in first steps of EEMD have already included the most essential feature of original data. Thus IMFs in first steps of EEMD are chosen to extract the fault feature. The steps of EEMD IMFs decomposition and energy entropy are described as follows:

(1) Process an EEMD for the original signal, and pick out first *n* IMFs which include the fault essential features.

(2) Compute each IMF energy by

$$E_i=\int_{-\infty}^{+\infty}|c_i(t)|^2dt \quad (i=1,2,\cdots,S) \tag{4}$$

(3) Construct feature vector which element represents IMFs energy.

$$T=[E_1, E_2, ...E_S] \tag{5}$$

(4) Normalize the feature vector T: the sum of IMFs energy is defined as:

$$E=\left(\sum_{i=1}^{S}|E_i|^2\right)^{1/2} \tag{6}$$

(5) And the normalized feature vector T' can be described as:

$$T'=\left[E_1/E, E_2/E, \cdots, E_S/E\right] \tag{7}$$

T' is the final input feature vector of LSSVM classification.

III. Least Squares Support Vector Machine

A. Least Squares Support Vector Machine Principle

LSSVM is an improvement of SVM, which replace the insensitive loss function of SVM with a quadratic loss function [10-11]. By constructing a quadratic loss function, the second classification optimization in SVM is transformed as a quadratic equation solution problem, in which way, decreases the complexity of computing and gains a better character on noise resistance and training speed. The basic principle and implementation steps of LSSVM refer to the reference [12-13]. In brief, the complex compute in high-dimensional feature space is replaced by inner product calculation of the kernel function, which avoids the dimensionality curse in high-dimensional feature space calculation. The maximum dimension of linearity classification facet VC is determined by the dimension of the feature space. By adjusting different parameters, the dimension of the feature space can be changed, which decides the minimum empirical error of linearity classification facet. In a word, different type of kernel function decides different features of LSSVM.

RBF kernel function $k(x,x_i)=\exp(-\|x-x_i\|^2/\sigma^2)$ is to prove the performance efficient compared with other kernel functions in identification and decision [14], thus RBF kernel function is selected for constructing LSSVM.

B. Chaotic Particle Swarm Optimization Algorithm

In the D-dimensional search space, the position and velocity of particle can be described as $x_i=(x_{i1},x_{i2},...,x_{iD})$ and $V_i=(v_{i1},v_{i2},...,v_{iD})$, and the best previous position of particle is recorded as $P_i=(p_{i1},p_{i2},...,p_{iD})$. Then all the best positions for particles are constructed as a set. The velocity and position of each generation particle can be update according to the (8) and (9) [15-18]:

$$v_{id}(k+1)=\omega v_{id}(k)+c_1r_1(p_{id}(k)-x_{id}(k))+c_2r_2(p_{gd}(k)-x_{id}(k)) \tag{8}$$

$$x_{id}(k+1)=x_{id}(k)+v_{id}(k+1) \tag{9}$$

Where k represents the iterations; ω represents inertia weight; c_1 and c_2 are acceleration coefficients, as well as r_1 and r_2 are acceleration parameters with range $[0,1]$.

Although the standard particle swarm optimization algorithm (PSO) is easy to use, it can easily trap into local optimum and converge slowly in later generation. In order to improve searching ability and avoid being trapped into local optimum, chaos theory is applied to improve the PSO algorithm, which is called CPSO algorithm. Due to the randomness, ergodicity and sensibility for the initial condition of the chaotic motion, both the ability to skip out of local optimum, and the convergence rate and precision of the CPSO algorithm are improved [19-20].

In order to lead into the chaotic motion, a logistic model is introduced to the standard particle swarm algorithm, which is described as follows [21-23]:

$$x_{n+1}=\mu * x_n *(1-x_n) \qquad n=0,1,2,\cdots,N \tag{10}$$

Where μ is the chaos coefficient; n is iteration coefficient, and x_n is a variable. The solution period of equation will be infinitely great, which results in an uncertain solution, when $3.5714\le\mu\le 4$. At this time, logistic takes the mapping into a chaotic state. p_{gd} is mapped to [0,1], the domain of definition for logistic equation is gained as follows[24-25]:

$$y=(p_{gd}-R_{\min})/(R_{\max}-R_{\min}) \tag{11}$$

$R_{\max}$ and $R_{\min}$ represent the upper bound and lower bound respectively. Assume the chaos sequence for M-th generation is $y=(y_1,y_2,...,y_M)$, and then a mapping can be computed by (12):

$$p_{gd,m} = R_{min} + y_m(R_{max} - R_{min}) \quad m = 1,2,\cdots,M \qquad (12)$$

A new particle feasible solution sequence is gained as below:

$$p^*_{gd} = (p^*_{gd,1}, p^*_{gd,2}, \ldots, p^*_{gd,M},) \qquad (13)$$

Therefore, owing to the global ergodicity of chaotic particle, a chaotic ergodic process is conducted according to the principle of chaotic motion after the iterative solution for every particle, which is used to search the whole space instead of staying in the local optimum.

IV. CPSO-LSSVM Model with RBF Kernel Function

The CPSO algorithm based on LSSVM with RBF kernel function need to optimize two parameters: kernel function parameter γ and penalty coefficient σ . Then initialize optimization steps are represented as follows:

(1) System initialization. The scale of particle swarm is set as *m=20*. And particle position (γ,σ) randomly.

(2) Determine the range of optimized parameters, and set the maximum speed. Penalty coefficient σ is used to balance the model complexity and approximate error, which means a greater σ represents a higher degree of fitting. γ is a parameter used to reflect the connection between support vectors. Considering reference [15] and several trial results, the range of (γ,σ) is set to $\{0.01,1000;0.01,1000\}$.

(3) Build a CPSO-LSSVM model, and calculate the fitness function $F(x_i)$ $i = 1,2,\cdots,m$ for each particle. $F(x_i)$ is applied to compare with local optimum value $F(P_{best_i})$ then. If $F(x_i) < F(p_{best_i})$, the former generation $F(P_{best_i})$ is replaced by x_i . Fitness function is described as below:

$$F(x_i) < \frac{1}{m}\sum_{i=1}^{m}\frac{|f_r|}{f_r + f_w} \qquad (14)$$

Where f_c represents the right fault identification, and f_c represents the wrong fault identification.

(4) Compare the best fitness function for each particle $F(x_i)$ to that for all the particles $F(G_{best_i})$. If $F(x_i) < F(G_{best_i})$, the swarm best position G_{best_i} is replaced by x_i .

(5) Refresh the particle position and speed, as well as inertia weight coefficient ω .

(6) Judge the terminal condition. Check the iterations whether meets T = 200; or check the fitness function $F(x_i) < 1\times10^{-4}$. If so, terminate the optimization.

(7) Calculate the optimum parameters, and then build the CPSO-LSSVM sensor fault identification model with the optimum values of (γ,σ) .

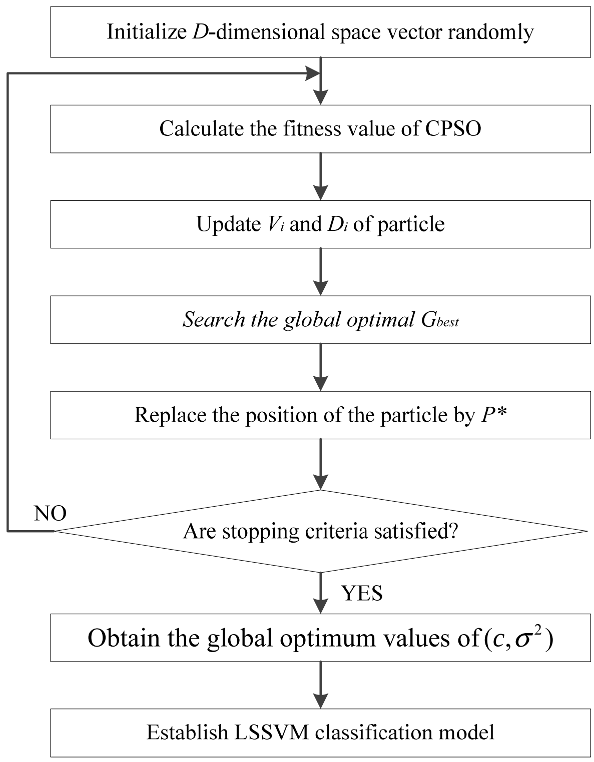

Figure 1. Flow Chart of LSSVM optimized by CPSO

V. Examples and Analysis

A. Feature Extraction

The fault diagnosis flow chart of sensor based on EEMD energy entropy and LSSVM is shown in Figure 2. Firstly the original output signal is decomposed with EEMD according to (1)-(3), and IMFs energy can be achieved according to (4)-(7). Then the feature vector is concluded after normalization process. At last, sensor failure types are identified by optimized LSSVM

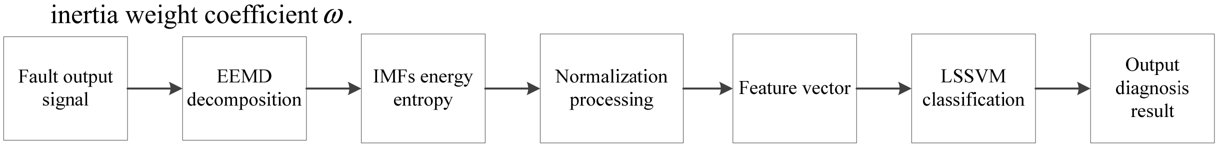

Figure 2. Flow chart of sensor fault diagnosis

The proposed fault diagnosis algorithm in this paper is confirmed by an example of the fault diagnosis for pressure sensor of electric multiple units (EMUs), which is used to measure the brake control system air spring pressure of CRH2 EMUs. According to the data in bias, spike, drift, cyclic, erratic and stuck (Figure 3), an EEMD process is conducted for every 150 sets of data in every fault type, following the steps proposed in Section 2.1. Then the IMFs energy feature vector is extracted and 100 sets of are selected among them randomly, used for the input of LSSVM classification training, while 50 sets of data for fault diagnosis. As EEMD is a principal component analysis method, and IMFs gained in first steps of EEMD has already included the most essential feature of original data, the first 8 IMFs components are chosen.

The simulation spike failure of pressure sensor is shown in Figure 4. Figure 5 is EMD waveform of spike failure. It includes 8 IMFs and residual items, and has mode mixing during the EMD, which influence the accuracy of fault feature extraction. Figure 6 is the waveform of EEMD, which includes 8IMFs and residual items, and without mode mixing. Each IMF indicates the different fault information.

The energy distributions for 8 IMFs components are calculated respectively in seven fault states, and eigenvector matrix is built by normalization operation. In order to compare with other fault feature extraction methods, part of the experiment data are shown in TABLE I and TABLE II, which applied with wavelet packet energy entropy extraction method and EMD energy entropy extraction method. TABLE III lists pressure sensor feature vector of seven fault state.

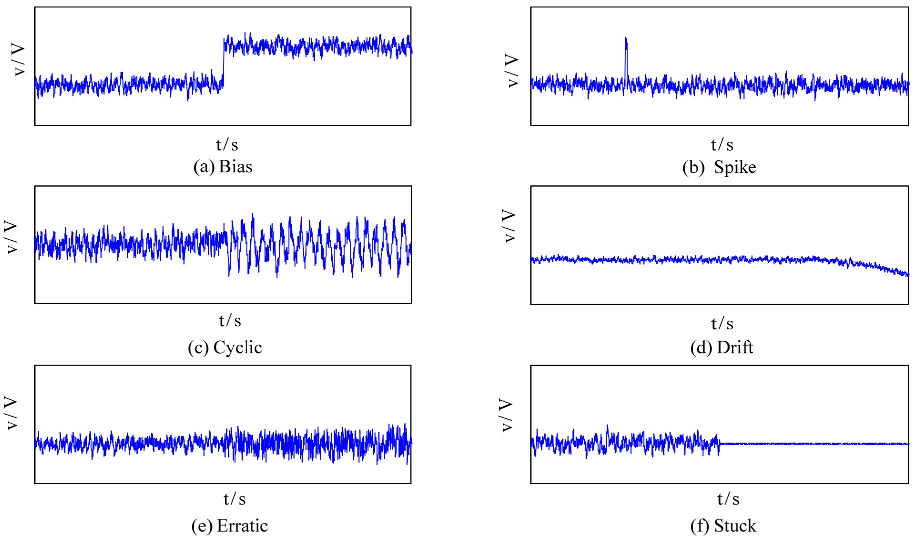

Figure 3. Pressure sensor fault output voltage signal

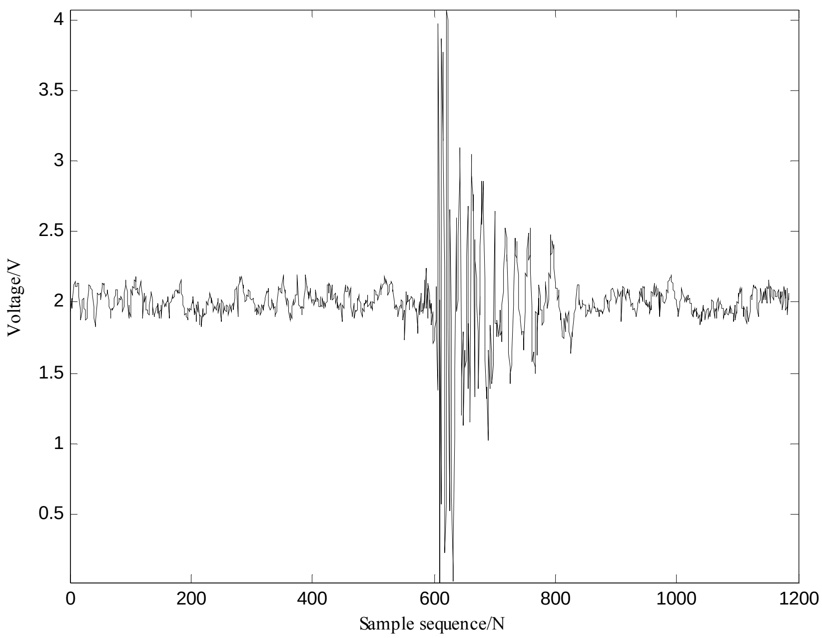

Figure 4. Waveform of simulation spike failure

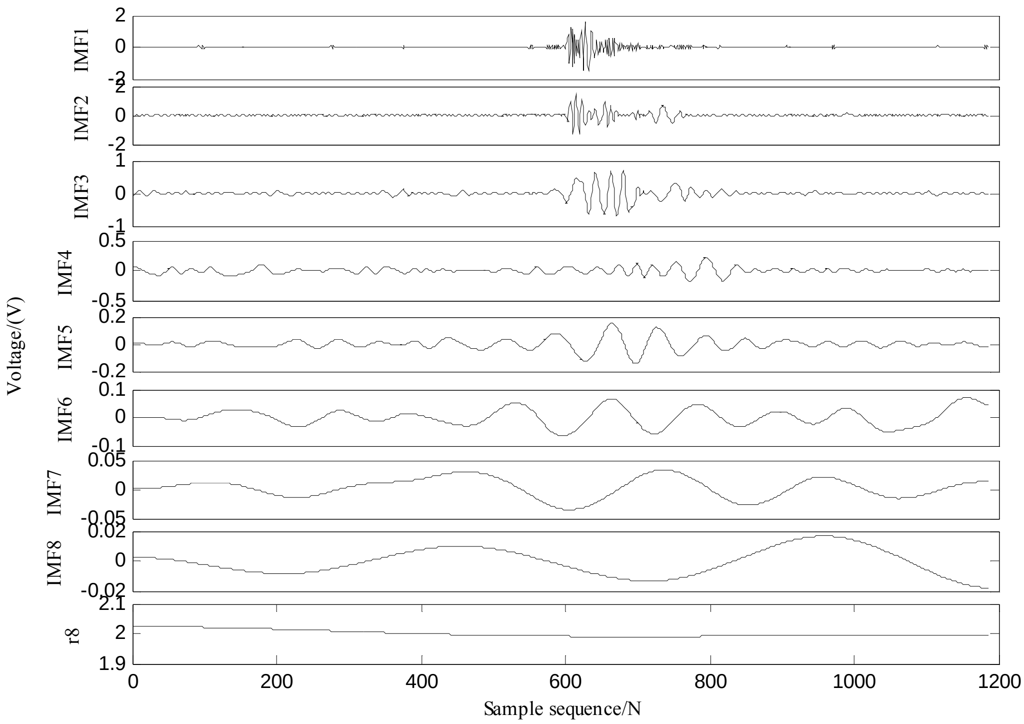

Figure 5. EMD waveform of spike failure

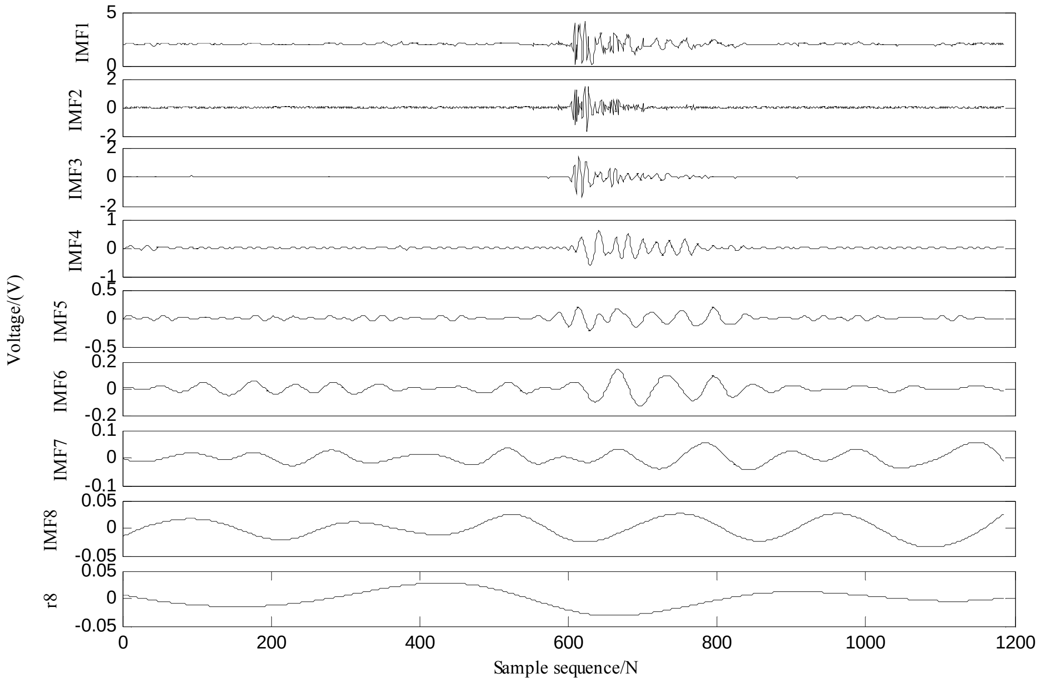

Figure 6. EEMD waveform of spike failure

B.Parameters Optimization

The penalty coefficient γ and kernel function parameter σ of LSSVM are optimized with CPSO algorithm. The detail optimized parameters are set as following: the number of particle is 20; the learning coefficients $r_1 = r_2$ are constantly equal to 2.05; the maximum iterations $k_{\max} = 500$; and the initial inertia weight $\omega_{\max} = 0.95$, $\omega_{\min} = 0.35$ .The penalty coefficient γ and kernel function parameters σ are optimized according to the flow of Fig.1,and then the optimization results are $\gamma = 108.245$ and $\sigma = 1.436$.

TABLE I.
THE PART OF SENSOR FEATURE VECTOR UNDER DIFFERENT FAULT TYPES BY WPT

Type of speed sensor fault	E_1/E	E_2/E	E_3/E	E_4/E	E_5/E	E_6/E	E_7/E	E_8/E
Nomal	0.731 0.729 ⋮ 0.729	0.350 0.345 ⋮ 0.354	0.278 0.284 ⋮ 0.279	0.281 0.279 ⋮ 0.283	0.271 0.254 ⋮ 0.258	0.243 0.249 ⋮ 0.238	0.194 0.193 ⋮ 0.195	0.093 0.086 ⋮ 0.098
Bias	0.994 0.994 ⋮ 0.992	0.066 0.045 ⋮ 0.058	0.048 0.044 ⋮ 0.048	0.046 0.044 ⋮ 0.040	0.043 0.042 ⋮ 0.035	0.038 0.035 ⋮ 0.035	0.034 0.031 ⋮ 0.028	0.019 0.014 ⋮ 0.017
Spike	0.842 0.834 ⋮ 0.841	0.268 0.271 ⋮ 0.265	0.240 0.234 ⋮ 0.241	0.210 0.204 ⋮ 0.211	0.179 0.183 ⋮ 0.180	0.182 0.178 ⋮ 0.177	0.136 0.141 ⋮ 0.138	0.085 0.091 ⋮ 0.087
Drift	0.999 0.999 ⋮ 0.998	0.008 0.007 ⋮ 0.009	0.007 0.007 ⋮ 0.007	0.004 0.005 ⋮ 0.004	0.004 0.003 ⋮ 0.004	0.003 0.003 ⋮ 0.002	0.002 0.003 ⋮ 0.002	0.002 0.001 ⋮ 0.002
Cyclic	0.912 0.924 ⋮ 0.911	0.214 0.187 ⋮ 0.212	0.179 0.181 ⋮ 0.176	0.168 0.154 ⋮ 0.164	0.167 0.153 ⋮ 0.162	0.161 0.148 ⋮ 0.157	0.115 0.108 ⋮ 0.112	0.087 0.065 ⋮ 0.074
Erratic	0.409 0.411 ⋮ 0.408	0.408 0.410 ⋮ 0.408	0.399 0.400 ⋮ 0.398	0.387 0.378 ⋮ 0.386	0.384 0.374 ⋮ 0.382	0.334 0.341 ⋮ 0.331	0.271 0.270 ⋮ 0.268	0.132 0.128 ⋮ 0.134
Stuck	0.735 0.734 ⋮ 0.739	0.346 0.347 ⋮ 0.351	0.298 0.301 ⋮ 0.297	0.268 0.267 ⋮ 0.270	0.266 0.265 ⋮ 0.269	0.248 0.245 ⋮ 0.247	0.195 0.196 ⋮ 0.194	0.101 0.098 ⋮ 0.104

TABLE II.
THE PART OF SENSOR FEATURE VECTOR UNDER DIFFERENT FAULT TYPES BY EMD

Type of speed sensor fault	Feature vector						
Nomal	0.519 0.521 ⋮ 0.517	0.365 0.364 ⋮ 0.366	0.501 0.503 ⋮ 0.499	0.412 0.414 ⋮ 0.411	0.291 0.292 ⋮ 0.290	0.287 0.285 ⋮ 0.284	0.674 0.677 ⋮ 0.676
Bias	0.085 0.086 ⋮ 0.089	0.065 0.064 ⋮ 0.068	0.084 0.087 ⋮ 0.085	0.091 0.092 ⋮ 0.094	0.102 0.106 ⋮ 0.105	0.982 0.984 ⋮ 0.981	0.687 0.683 ⋮ 0.688
Spike	0.352 0.354 ⋮ 0.351	0.317 0.318 ⋮ 0.316	0.450 0.448 ⋮ 0.426	0.438 0.437 ⋮ 0.435	0.382 0.379 ⋮ 0.377	0.425 0.423 ⋮ 0.428	0.836 0.837 ⋮ 0.834
Drift	0.009 0.008 ⋮ 0.007	0.007 0.007 ⋮ 0.008	0.007 0.008 ⋮ 0.007	0.006 0.006 ⋮ 0.005	0.009 0.011 ⋮ 0.008	0.998 0.997 ⋮ 0.999	0.782 0.778 ⋮ 0.774
Cyclic	0.319 0.321 ⋮ 0.318	0.554 0.556 ⋮ 0.555	0.657 0.651 ⋮ 0.654	0.273 0.274 ⋮ 0.276	0.185 0.189 ⋮ 0.182	0.181 0.179 ⋮ 0.182	0.689 0.690 ⋮ 0.687
Erratic	0.736 0.736 ⋮ 0.740	0.467 0.461 ⋮ 0.468	0.339 0.340 ⋮ 0.335	0.261 0.264 ⋮ 0.264	0.178 0.177 ⋮ 0.174	0.201 0.204 ⋮ 0.199	0.753 0.759 ⋮ 0.756
Stuck	0.532 0.533 ⋮ 0.530	0.378 0.381 ⋮ 0.376	0.465 0.461 ⋮ 0.467	0.425 0.426 ⋮ 0.426	0.302 0.304 ⋮ 0.304	0.298 0.299 ⋮ 0.301	0.801 0.798 ⋮ 0.803

TABLE III.
THE PART OF SENSOR FEATURE VECTOR UNDER DIFFERENT FAULT TYPES BY EEMD

Type of speed sensor fault	E_1/E	E_2/E	E_3/E	E_4/E	E_5/E	E_6/E	E_7/E	E_8/E
Nomal	0.731	0.350	0.278	0.281	0.271	0.243	0.194	0.093
	0.732	0.349	0.277	0.280	0.272	0.244	0.194	0.092
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	0.733	0.350	0.276	0.283	0.269	0.241	0.192	0.094
Bias	0.994	0.066	0.048	0.046	0.043	0.038	0.034	0.019
	0.993	0.065	0.049	0.045	0.044	0.038	0.031	0.020
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	0.995	0.062	0.047	0.045	0.042	0.039	0.035	0.018
Spike	0.842	0.268	0.240	0.210	0.179	0.182	0.136	0.085
	0.841	0.269	0.241	0.211	0.178	0.183	0.137	0.086
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	0.839	0.267	0.240	0.212	0.180	0.181	0.138	0.086
Drift	0.999	0.008	0.007	0.004	0.004	0.003	0.002	0.002
	0.999	0.008	0.005	0.005	0.004	0.003	0.003	0.002
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	0.998	0.007	0.006	0.006	0.004	0.003	0.003	0.001
Cyclic	0.912	0.214	0.179	0.168	0.167	0.161	0.115	0.087
	0.914	0.215	0.180	0.166	0.165	0.160	0.114	0.089
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	0.911	0.216	0.176	0.169	0.166	0.159	0.115	0.088
Erratic	0.409	0.408	0.399	0.387	0.384	0.334	0.271	0.132
	0.410	0.409	0.398	0.385	0.383	0.332	0.273	0.133
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	0.407	0.407	0.396	0.389	0.385	0.335	0.274	0.131
Stuck	0.735	0.346	0.298	0.268	0.266	0.248	0.195	0.101
	0.736	0.347	0.299	0.265	0.264	0.245	0.198	0.103
	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
	0.734	0.348	0.300	0.267	0.266	0.247	0.197	0.102

C. Experiment Analysis

In order to compare the identification performance for the fault features of method proposed and methods, eight energy entropy features are achieved in the EEMD process in 700 sets of data, 100 for each state. Then 50 sets of data are input to the LSSVM for training, while the others are used for test. The comparison results are shown in TABLE IV.

To compare the identification ability of different methods, 50 sample sets of data for each sensor fault are used to train the classifiers, and the other 50 sets of data to sensor fault identification. Compared with the methods based on WPT, EMD and EEMD could diagnose the sensor fault efficient as preprocessor, TABLE IV shows that the LSSVM based on EEMD is superior to those based on WPT and EMD in classification. This is because that the EEMD decomposition is a self-adaptive and can avoid the mode mixing effect compared to the EMD decomposition, and the WPT decomposition is not self-adaptive, that is the frequency components after decomposition would not change with the fault signal.

TABLE IV.
COMPARISON OF DIAGNOSTIC RESULTS AMONG DIFFERENT METHODS

Method	Training samples	Diagnosis samples	Identification results						
			Normal	Bias	Spike	Drift	Cyclic	Erratic	Stuck
WPT-BPNN	50	50	38	39	41	40	38	41	43
EMD-SVM	50	50	48	50	46	49	47	48	49
EEMD-LSSVM	50	50	50	50	49	49	50	50	50

TABLE V.
COMPARISON OF DIAGNOSTIC RESULTS UNDER SMALL SAMPLES

Method	Training samples	Diagnosis samples	Identification results						
			Normal	Bias	Spike	Drift	Cyclic	Erratic	Stuck
WPT-BPNN	10	30	18	20	20	19	17	18	22
EMD-SVM	10	30	28	27	24	28	26	27	28
EEMD-LSSVM	10	30	29	30	26	27	28	29	29

According to the results in TABLE V, EEMD-LSSVM can diagnose the sensor fault in a higher accuracy among EEMD-LSSVM, EMD-SVM and WPT-BPNN, and the fault diagnosis strategy based on energy entropy feature with EEMD is validly. 10 sets of original sensor output data is taken in the example as a kind of small sample situation. EEMD-LSSVM performs better in identification accuracy of seven different sensor faults than EMD-SVM and WPT-BPNN of small sample situation.

VI. CONCLUSION

In order to diagnose the sensor fault, EEMD energy entropy is preprocessed to the sensor output fault signal, which performs very well in noise reduction and detail features extraction. An eigenvector that represents the energy distribution in different fault patterns can be achieved by extracting the IMFs energy entropy of EEMD. Then a training and identification method is presented for pressure sensor of EMUs by optimized LSSVM with the parameters is optimized by CPSO algorithm. According to the theory analysis and experiment results, the extracted feature has a good separability and robustness for the sensor fault identification.

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