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A Novel Fault Diagnosis Method for Acceleration Sensor Utilizing IEM-Based LLE and WKELM

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1. Introduction

Acceleration sensor is used to acquire the vibration signal of mechanical equipment, which is very important to detect the state of mechanical equipment, which can improve equipment security and reliability [1-5]. The complex features of output signals of acceleration sensor behavior pose serious challenges to establish effective fault diagnosis for acceleration sensor [6-8]. As the numerous features of acceleration sensor data can affect diagnosis accuracy and diagnosis speed, the features of acceleration sensor data must be reduced. Recently, there are a lot of dimensionality reduction algorithms, such as include local linear embedding (LLE) algorithm, PCA [9, 10]. As there is poor ability of current dimensionality reduction algorithms in the processing of acceleration sensor data, an LLE algorithm based on IEM is proposed to reduce the features of acceleration sensor data, which can address the impact of misaligned sample position differences.

In order to improve the fault diagnosis for acceleration sensor ability of extreme learning machine (ELM), a weighted kernel ELM algorithm using kernel functions is beneficial for improving the robustness and nonlinear processing ability of the traditional weighted ELM. Finally, the feasibility of fault diagnosis method for acceleration sensor of IEM-based LLE and weighted ELM to identify acceleration sensor is testified. The testing results illustrate that shows that the diagnosis accuracy for acceleration sensor by using IEMLLE-WKELM is 99.375%, the diagnosis accuracy for acceleration sensor by using LLE-WKELM is 95.625%, the diagnosis accuracy for acceleration sensor by using LLE-ELM is 94.375%, and the diagnosis accuracy for acceleration sensor by using PCA-ELM is 92.5%, it is concluded that IEMLLE-WKELM is the higher diagnosis accuracy for acceleration sensor than other methods.

Firstly, IEM-based LLE algorithm is introduced. Secondly, weighted kernel extreme learning machine is introduced. Thirdly, experimental analysis is introduced. Finally, conclusions are introduced.

2. IEM-based LLE Algorithm

In the dimensionality reduction process of LLE algorithm [13], Euclidean distance is used to select the nearest neighbor in the processing of feature extraction, there is a significant problem of the position difference of misaligned samples. An LLE algorithm based on IEM is proposed to address the impact of misaligned sample position differences, among which information entropy can solve the problem of information quantification. Given high dimensional dataset $X = (x_1, x_2, \ldots, x_L)$ (x_i represents any sample point with N features), calculate the information entropy $E(x_i)$,

$$E\left(x_i\right) = -\sum_{i=1}^{N} P_{x_{ij}} \left(log_2 P_{x_{ij}}\right), \tag{1}$$

where $P_{x_{ij}}$ is the appearing probability.

The entropy difference is calculated as follows:

$$D_e = E\left(x_i\right) - E\left(x_j\right). \tag{2}$$

Select k nearest neighbors of a sample by using entropy difference. The reconstruction weight coefficient w'_{ij} is calculated as follows:

$$L(w) = min\left\| x_i - \sum_{j\in k} w'_{ij} x_{ij} \right\|_2^2. \tag{3}$$

Reconstruct the vector z using w'_{ij} to minimize quadratic form, which is expressed as follows:

$$L\left(z\right) = min\left\| z_i - \sum_{j=1}^{R} w'_{ij} z_{ij} \right\|_2^2,$$

$$s.t. \quad \begin{cases} \sum_{i=1}^{R} w'_{ij} z_{ij} = RI \\ \sum_{i=1}^{R} z_i = 0 \end{cases}. \tag{4}$$

Then, calculate the corresponding low dimensional embedding results as follows:

$$\begin{cases} L\left(Z\right) = tr\left(ZVZ^T\right) \\ V = \left(I - w\right)^T \left(I - w\right) \end{cases}. \tag{5}$$

Fig. 1 gives the comparison of the distribution of two classes between IEMLLE and LLE.

As shown in Fig. 1, the IEMLLE’s discrimination rate of the two types of data based on is higher than that that of LLE. Obviously, the LLE algorithm based on IEM helps to address the impact of misaligned sample position differences.

3. Weighted Kernel Extreme Learning Machine

An ELM model is given as follows [14]:

$$g(x)=m(x)M^T\left(I/C+MM^T\right)^{-1}T\ , \qquad (6)$$

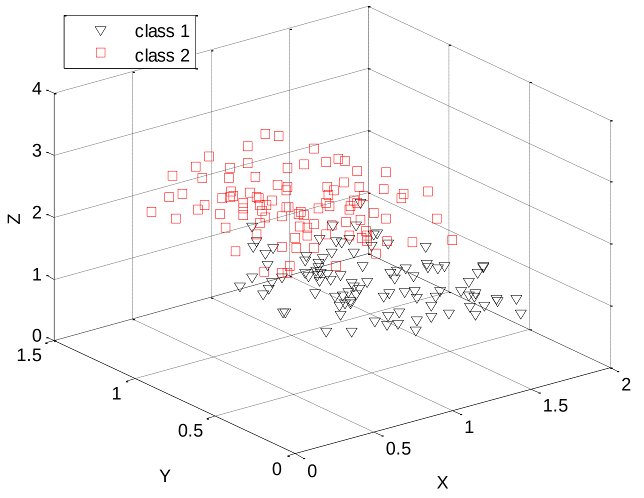
where $M=\left[m(x_1),\cdots,m(x_N)\right]^T$ is the hidden layer feature mapping matrix; $T=\left[t_1,\cdots,t_N\right]^T$ is the training objective matrix.

The weighted cumulative error of each sample is minimized as follows:

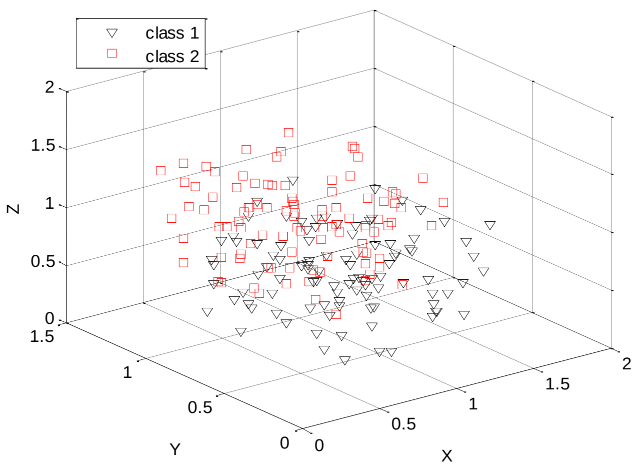
$$\min\frac{1}{2}\left[\left\|\alpha\right\|^2+CW\sum_{i=1}^{N}\left\|\xi_i\right\|^2\right],$$

$$s.t.\ \ m(x_i)\alpha=t_i^T-\xi_i^T\ , \qquad (7)$$

where W is the diagonal matrix, ξ_i is the error, and the ELM's weight is given as Eq. (8) after adding I/C to the main diagonal of MM^T,



a



b

Fig. 1 Comparison of the distribution performance between IEMLLE and LLE: a – the data distribution of two classes based on IEMLLE, b – the data distribution of two classes based on LLE

$$\alpha=M^T\left(I/C+MM^T\right)^{-1}T\ , \qquad (8)$$

where C is the penalty parameter and I is the identity matrix.

The weighted extreme learning machine is described as Eq. (9) after introducing the kernel instead of MM^T,

$$g(x)=\begin{bmatrix}K(x,x_1)\\ \vdots \\ K(x,x_N)\end{bmatrix}^T\left[I/C+WK(x_i,x_j)\right]^{-1}WT\ , \qquad (9)$$

where $K(x_i,x_j)=\exp\left(-\varphi\left\|x_i-x_j\right\|^2\right)$ is the kernel function (ϕ is kernel parameter).

Obviously, C and ϕ need to be determined. In PSO algorithm, given the i-th particle's position x_i and the i-th particle's velocity v_i, the position and velocity of the particles are updated according to the follows [15]:

$$\begin{cases} v_{ij}^{t+1}=\omega\cdot v_{ij}^t+c_1\cdot r_1\cdot\left(pb_{ij}^t-x_{ij}^t\right)+ \\ \qquad +c_2\cdot r_2\cdot\left(gb^t-x_{ij}^t\right), \\ x_{ij}^{t+1}=x_{ij}^t+v_{ij}^{t+1}, \end{cases} \qquad (10)$$

where ω denotes the inertia weight; k denotes the iteration counter; r_1 and r_2 belong to 0 ~ 1; ($c_1=c_2=2$); pb_{ij} is the i-th particle's best previous position, and gb^t is the best particle among all the particles.

As PSO is prone to getting stuck in local optima,

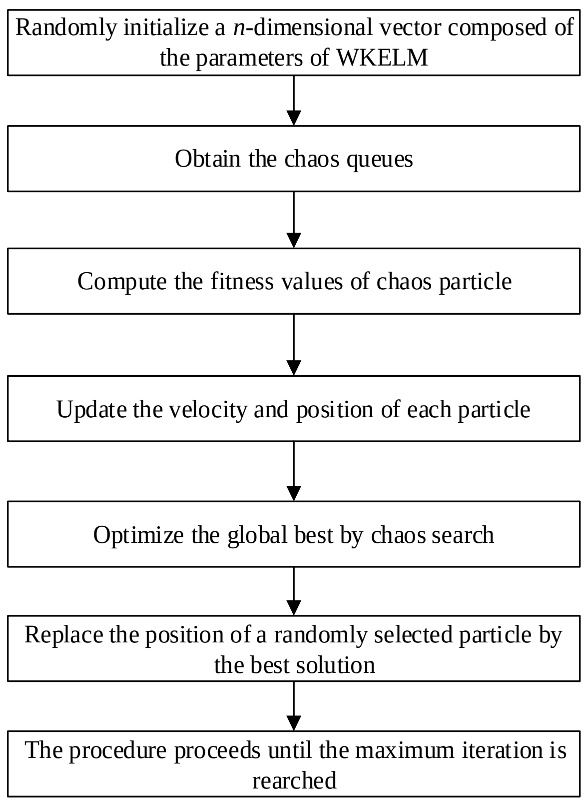


Fig. 2 Optimization process of the WKELM's parameters by using CPSO

chaotic dynamics is used to improve PSO, thereby avoiding falling into local optima. The chaotic queue is obtained by using the logistic equation,

$$b_{n+1} = \lambda b_n \left(1 - b_n\right), n = 0, 1, \cdots, N, \tag{11}$$

where b_n is a variable parameter ($0 \le b_0 \le 1$), and λ is the control parameter.

As shown in Fig. 2, the optimization process of the WKELM's parameters by using CPSO are given as follows:

Step 1 Initialize a n-dimensional vector randomly.

Step 2 Obtain the chaos queues by Eq. (11).

Step 3 Compute the chaos particle's fitness values.

Step 4 Each particle's velocity and position is obtained according to Eq.(10).

Step 5 The global best is optimized by chaos search, and the best solution p^* is obtained.

Step 6 Replace the position of a randomly selected particle by p^*.

Step 7 The procedure proceeds until the maximum iteration is reached. Otherwise, loop to step 3.

4. Experimental Analysis

In the study, the state types of the acceleration sensor include normal, offset fault, gain fault, drifting fault. In the experiment, 160 samples are used as the testing samples, and 40 samples are used in each state. Time-frequency images of the state types of acceleration sensor based on empirical wavelet transform are given in Fig. 3. Texture features of time-frequency images are employed.

C and ϕ are optimized by using CPSO, and the number of the particles is 20 in CPSO. The fault diagnosis model for acceleration sensor of IEM-based LLE and WKELM with CPSO is obtained. The comparison of the optimization process between CPSO and PSO is given in Fig. 4, and it can be seen that CPSO is better than PSO.

Fig. 5 gives the comparison of the actual results and fault diagnosis results for acceleration sensor of IEMLLE-WKELM,it can be seen that only one sample is incorrectly diagnosed by using IEMLLE-WKELM. Fig. 6 gives the comparison of the actual results and fault diagnosis results for acceleration sensor of LLE-WKELM, it can be seen that 7 samples are incorrectly detected by using LLE-WKELM. Fig. 7 gives the comparison of the actual results and fault diagnosis results for acceleration sensor of LLE-ELM, it can be seen that 9 samples are incorrectly diagnosed by using LLE-ELM. Fig. 8 gives the comparison of the actual results and fault diagnosis results for acceleration sensor of PCA-ELM, it can be seen that that 12 samples are incorrectly detected by PCA-ELM.

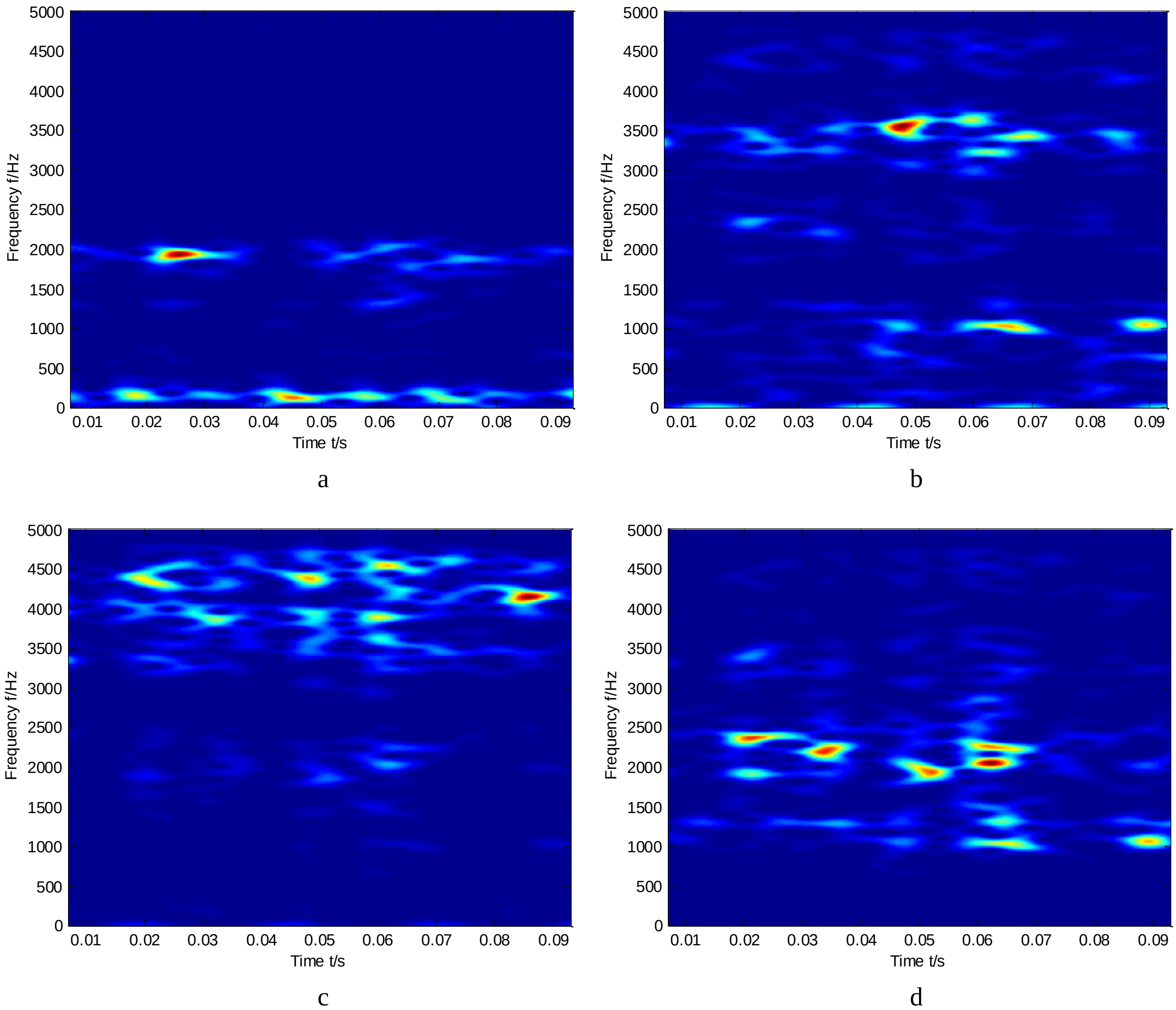


Fig. 3 Time-frequency images of the state types of acceleration sensor: a – normal state, b – offset fault, c – gain fault, d – drifting fault

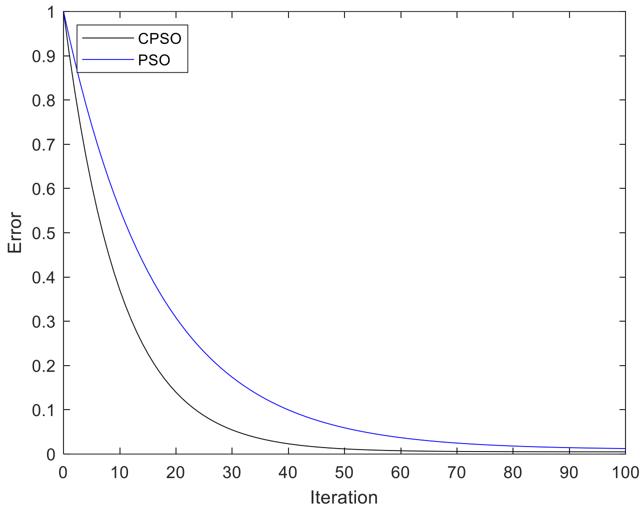


Fig. 4 Comparison of the optimization process between CPSO and PSO

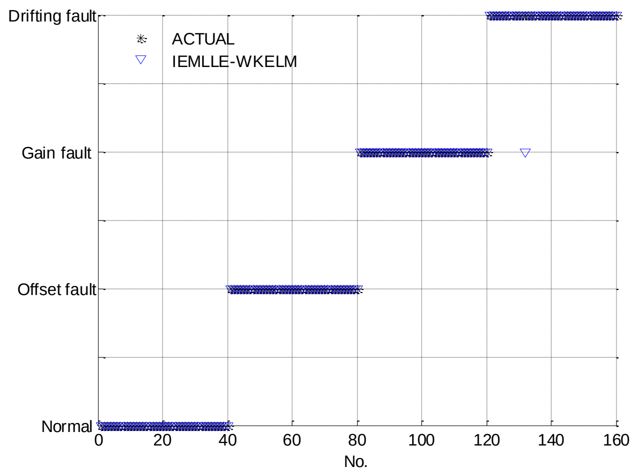


Fig. 5 Fault diagnosis results for acceleration sensor of IEMLLE-WKELM

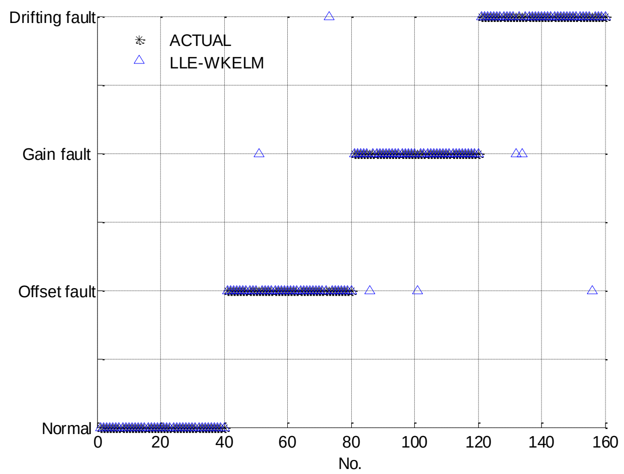


Fig. 6 Fault diagnosis results for acceleration sensor of LLE-WKELM

As shown in Table 1, the fault diagnosis accuracy for acceleration sensor by using IEMLLE-WKELM is 99.375%, the diagnosis accuracy for acceleration sensor by using LLE-WKELM is 95.625%, the diagnosis accuracy for acceleration sensor by using LLE-ELM is 94.375%, and the diagnosis accuracy for acceleration sensor by using PCA-ELM is 92.5%. The experimental results indicate that IEMLLE-WKELM is the higher fault diagnosis accuracy for acceleration sensor than other methods.

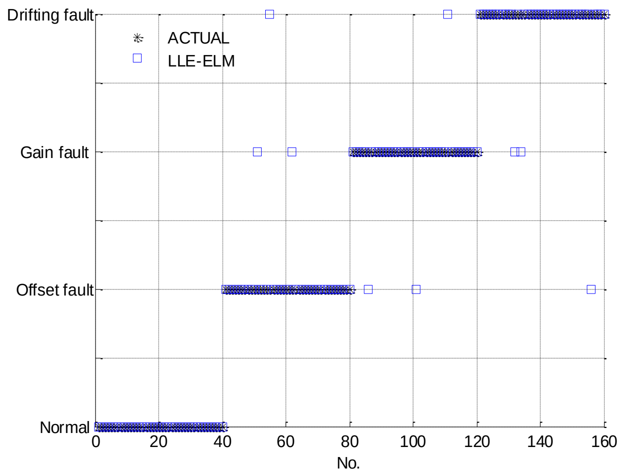


Fig. 7 Fault diagnosis results for acceleration sensor of LLE-ELM

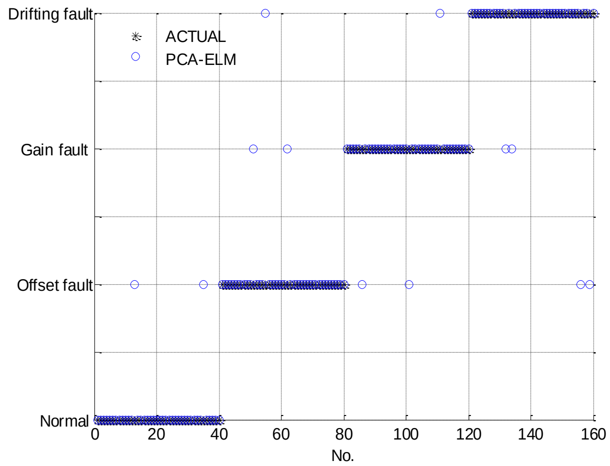


Fig. 8 Fault diagnosis results for acceleration sensor of PCA-ELM

Table 1

Comparison of the fault diagnosis results for acceleration sensor among IEMLLE-WKELM, LLE-WKELM, LLE-ELM, and PCA-ELM

Diagnosis algorithm	The total number of samples	The number of correct diagnosis	Diagnosis accuracy/%
IEMLLE-WKELM	160	159	99.375
LLE-WKELM	160	153	95.625
LLE-ELM	160	151	94.375
PCA-ELM	160	148	92.5

5. Conclusions

An LLE based on IEM called IEMLLE is presented to reduce the features of accelerometer data. The discriminative ability of IEMLLE based on the distribution of different categories of sample data is higher than that that of LLE.In addition, a WKELM algorithm is beneficial for improving the robustness and nonlinear processing capabilityof WKELM is proposed in this paper. Aiming at the local optimization problem of PSO algorithm, CPSO is presented to determine the penalty parameter and kernel parameter of WKELM, thereby avoiding falling into local optima. The experimental results show that shows that the fault diagnosis accuracy for acceleration sensor by using IEMLLE-WKELM is 99.375%, the diagnosis accuracy for acceleration sensor by using LLE-WKELM is 95.625%, the diagnosis accuracy for acceleration sensor by using LLE-ELM is 94.375%, and the diagnosis accuracy for acceleration sensor by using PCA-ELM is 92.5%, it is concluded that IEMLLE-WKELM is the higher fault diagnosis accuracy for acceleration sensor than other methods.

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Z. H. Gao

A NOVEL FAULT DIAGNOSIS METHOD FOR ACCELERATION SENSOR UTILIZING IEM-BASED LLE AND WKELM

S u m m a r y

In this study, fault diagnosis method for acceleration sensor by IEM-locally linear embedding and weighted kernel ELM (IEMLLE-WKELM) is proposed. An IEM-based LLE method is proposed to reduce the features of acceleration sensor data. The IEMLLE's discrimination rate of the two types of sample data is higher than that that of LLE. In addition, a weighted kernel ELM algorithm using kernel functions is beneficial for improving the robustness and nonlinear processing ability of the traditional weighted ELM is proposed. The testing results show that shows that the fault diagnosis accuracy for acceleration sensor by using IEMLLE-WKELM is 99.375%, the diagnosis accuracy for acceleration sensor by using LLE-WKELM for acceleration sensor is 95.625%, the diagnosis accuracy for acceleration sensor by using LLE-ELM is 94.375%, and the diagnosis accuracy for acceleration sensor by using PCA-ELM is 92.5%, it is concluded that IEMLLE-WKELM is the higher diagnosis accuracy for acceleration sensor than other methods.

Keywords: IEMLLE, weighted kernel extreme learning machine, fault diagnosis, acceleration sensor.

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