International Journal of Engineering

Journal Homepage: www.ije.ir

A Fault Diagnosis Method for Automaton Based on Morphological Component Analysis and Ensemble Empirical Mode Decomposition

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PAPER INFO

Paper history:
Received 08 January 2019
Received in revised form 14 March 2019
Accepted 02 May 2019

Keywords:
Automaton
Fault Diagnosis
Vibration Signal
Morphological Component Analysis
Ensemble Empirical Mode Decomposition

ABSTRACT

In the fault diagnosis of automaton, the vibration signal presents non-stationary and non-periodic, which make it difficult to extract the fault features. To solve this problem, an automaton fault diagnosis method based on morphological component analysis (MCA) and ensemble empirical mode decomposition (EEMD) was proposed. Based on the advantages of the morphological component analysis method in the signal separation, using the morphological difference of the components in the automatic vibration signal, different sparse dictionaries were constructed to separate the components, eliminates the noise components and extracted the effective fault characteristic component, the extracted impact components are decomposed by EEMD and the energy feature of each IMF component is calculated as the fault features, then put the fault features into SVM (Support Vector Machine) and identify the faults. Through the construction simulation example and the typical fault simulation test of automatic machine, it showed that the morphological component analysis method had better noise reduction and signal separation effect. Compared with the traditional EEMD method, the feature extraction method based on the MCA-EEMD can distinguish automaton fault types more effectively.

doi: *10.5829/ije.2019.32.06c.12*

1. INTRODUCTION

Automaton is the core part of the antiaircraft weapon system, it contains numerous parts and the mechanism movement of automaton is complex. Because of the high load and badly working environment (high temperature, high pressure), the automaton is prone to a series of faults and failures, such as wear, ablation and fatigue occurred in components. The vibration signal contains abundant running state information in the mechanical system [1], acquiring the vibration signal from automaton for feature extraction is an important method for fault diagnosis.

When a fault occurs in automaton, the vibration signal measured is complex, non-stationary, non-linear, non-periodic and the vibration of automaton usually contains some unknown interference components and background noise. It is a challenge for automaton fault diagnosis because the weak fault characteristics is always submerged in signals with complex compositions. In recent years, researchers have proposed many effectively method to detect faults for automaton. Zhang and Pan [2] proposed a method based on empirical mode decomposition (EMD) and fuzzy C means clustering (FCM) to detect and identify automaton problems. Pan and Cui [3] used several chaotic parameters (correlation dimension, kolmogorov entropy) to extract the fault features in automaton fault diagnosis. Cao and Pan [4] used wavelet transform to extract the state characteristics to realize condition monitoring and fault diagnosis. However, the above methods extract features directly from the original vibration signal and do not consider separating effective components from the complex signals, these shortcomings make the accuracy of automaton fault diagnosis is not very satisfactory.

The automaton's operating characteristics determine that the impact component contains most of the fault information in the vibration signal, so the key to

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Please cite this article as: F. Wang, L. Fang, A Fault Diagnosis Method for Automaton Based on Morphological Component Analysis and Ensemble Empirical Mode Decomposition, International Journal of Engineering (IJE), IJE TRANSACTIONS C: Aspects Vol. 32, No. 6, (June 2019) 877-883

automaton fault diagnosis is to separate the impact component from original signal. Xu and Pan [5] used the independent component analysis (ICA) method to remove the interference signal and noise from automaton signals, but statistically independent assumptions components of ICA limited the separation effect. Starck and Robin [6] proposed morphological component analysis (MCA), it is a signal processing method based on sparse characterization. According to the differences in the morphological components of signals, different sparse representation dictionaries are used to separate the components in MCA. At first, MCA was applied to image processing [7]. In recent years, the MCA method has been applied in the field of mechanical signal analysis. Li et al. [8] used the MCA method to realize the effective separation of the gearbox vibration signal and improved the ability to extract transient shock signatures from a strong noise environment. Chen et al. [9] proposed the morphological component analysis method based on semi-soft threshold and achieved good results in the early stage of rubbing fault diagnosis of the rotor. Xu et al. [10] applied the double tree complex wavelet noise reduction method based on morphological component analysis (MCA) to gear fault diagnosis and obtained clear fault feature frequency, which provided a new method for early fault feature extraction of gears.

EEMD method was first introduced by Huang et al. [11], it is a self-adaptive decomposition method and is an improved form of EMD method that can effectively solve the modal aliasing defects existing in the EMD method, EEMD has a good performance for feature extraction in the machinery vibration signals.

In this paper, we proposed an effective method for automatic machine fault diagnosis. Firstly, the MCA method is applied to the preprocessing of automatic vibration signals to achieve noise reduction and separate the impact components from complex original signal. After that, the EEMD method is used to analyze the impact component, then the energy of the several IMFs is obtained as fault features. Finally, the fault features were entered into the support vector machines (SVM) for fault type identification.

2. TECHNICAL BACKGROUND

2. 1. The Review of Morphological Component Analysis

MCA is a sparse decomposition method based on the morphological diversity of signal components. The specific principle is as follows:

Assume that the real signal $\mathbf{S}$ is a linear combina tion of N different forms of signal $\mathbf{s_n} : \mathbf{S} = \sum_{n=1}^{N} s_n$. Ea ch of the components s_n can be represented by a c orresponding dictionary $\mathbf{\Phi_n}$, namely, $\mathbf{s_n} = \mathbf{\Phi_n \alpha_n}$, $\mathbf{\alpha_n}$ is the decomposition factor, $\mathbf{\Phi_n}$ is an over complete d ictionary and can only sparsely express $\mathbf{s_n}$.

The sparse representation of $\mathbf{S}$ was converted to the optimal solution of the following relation:

$$\min_{\{\alpha_1 \dots \alpha_n\}} \sum_{n=1}^{N} \|\mathbf{\alpha_n}\|_1 \quad \text{subject to: } \mathbf{S} = \sum_{n=1}^{N} \mathbf{\Phi_n \alpha_n} \tag{1}$$

Equation (1) can be converted to the following form:

$$[\mathbf{s_1}, \dots, \mathbf{s_n}] = \arg \min_{\{\alpha_1, \dots, \alpha_n\}} \sum_{n=1}^{N} \|\mathbf{\alpha_n}\| + \lambda \left\| S - \sum_{n=1}^{N} \mathbf{\Phi_n \alpha_n} \right\|_2^2 \tag{2}$$

In Equation (2), λ is the given threshold. When the overcomplete dictionary is known, the sparse representation of $\mathbf{s_n}$ is as follows:

$$\mathbf{s_n} = \mathbf{\Phi_n^{\lambda} \alpha_n} \tag{3}$$

In Equation (3), $\Phi_n^{\lambda} = \Phi_n^T \left(\Phi_n \Phi_n^T\right)^{-1}$, the solution of α_n can be converted to the solution of each $[\mathbf{s_1}, \dots, \mathbf{s_n}]$:

$$[\mathbf{s_1}, \mathrm{L}\ , \mathbf{s_n}] = \arg \min_{\{\alpha_1, \mathrm{L}\ , \alpha_n\}} \sum_{n=1}^{N} \|\mathbf{\alpha_n}\| + \lambda \left\| \mathbf{s} - \sum_{n=1}^{N} \mathbf{\Phi_n \alpha_n} \right\|_2^2 \tag{4}$$

From the implementation process of morphological component analysis, the threshold is continuously updated based on an increase in the number of iterations. At present, there are mainly three threshold processing methods for transform coefficients: soft threshold method, hard threshold method and semi-soft threshold method.

The soft threshold method is:

$$\alpha_n' = \begin{cases} \operatorname{sgn}(\alpha_n)(|\alpha_n| - \delta_n) & |\alpha_n| \geq \delta \\ 0 & |\alpha_n| < \delta \end{cases} \tag{5}$$

Among them, $\operatorname{sgn}(x)$ is a symbolic function, that is, when $x > 0$, the value is 1 and when $x < 0$, the value is -1. Soft thresholding method can ensure the continuity of the signal, but it may weaken the useful signal and lead to poor decomposition.

Hard threshold method:

$$\alpha_n' = \begin{cases} \alpha_n, & |\alpha_n| \geq \delta \\ 0, & |\alpha_n| < \delta \end{cases} \tag{6}$$

The hard threshold method is not continuous at the threshold point, which will give the signal a large variance.

For the shortcomings of soft threshold processing and hard threshold processing, Gao and Brucc [12] proposed a semi-soft threshold method, as shown in Equation (7).

$$\alpha_n = \begin{cases} 0 & |\alpha_n| \le \delta_{n1} \\ \mathrm{sgn}(\alpha_n) \times \dfrac{\delta_{n2}(|\alpha_n| - \delta_{k1})}{\delta_{n2} - \delta_{n1}} & \delta_{n1} < |\alpha_n| \le \delta_{n2} \\ \alpha_n & |\alpha_n| < \delta_{n2} \end{cases} \tag{7}$$

In the formula, δ_{n2} is the upper threshold, δ_{n2} is the lower threshold, generally, $\delta_{n2} = 2\delta_{n1}$.

Compared with the soft threshold method and the hard threshold method, the semi-threshold method can reduce the mean square error more effectively while suppressing noise. In this paper, semi-soft threshold is used as the threshold of morphological component analysis.

2. 2. Ensemble Empirical Mode Decomposition (EEMD)

In the original EMD, the IMF components contain very different feature time scales or similar feature time scales distributed in different IMF components, this results in aliasing of two adjacent IMF waveforms and lead to modal aliasing phenomenon. EEMD method is mainly based on the principle that added white noise can populate the whole time–frequency space uniformly. According to the constituting components of different scales, when the signal is added with white noise, the signal will be continuous at different scales to reduce the degree of modal aliasing.

In EEMD method, there are two parameters that need to be decided. They are the number of ensemble *M* and the noise amplitude *a*. From the conclusion of the literature [13], when M = 100, a = 20%, EEMD has satisfying result. Hence, in this paper these two parameters were set as *M = 100, a = 20%.*

2. 3. Fault Feature Extraction: EEMD Energy Feature

When the signal is decomposed to several IMFs by EEMD, then selected the several IMF components based on the principle of correlation coefficient and calculated the energy feature. The method for calculating the energy of each IMF is as follows:

$$\begin{aligned} E_i &= \sum_{i=1}^{k} |f_i(t)|^2 \\ E &= \sum_{i=1}^{n} E_i \\ V_i &= E_i / E \end{aligned} \tag{11}$$

where, E_i is the energy of ith IMF, E is the sum of energies of IMFs and V_i represents the percentage of energy of ith IMF in the whole signal energy E.

3. SIMULATION ANALYSIS

In order to verify the effect of the morphological component analysis method on the separation of the impact components in the vibration signal, a synthetic simulation signal is constructed to analyze by MCA.

The synthetic signal is generated by harmonic components, impact components, and Gaussian white noise components. The harmonic components is produced by mixing a sine component with a frequency of 60 Hz and a cosine component with a frequency of 90 Hz, as shown in Figure 1(a), the impact signal is a series of impact components is show in Figure 1(b). The power of the added Gaussian white noise is 2dBW as shown in Figure 1(c). The sampling frequency of the synthetic simulation signal is 1024Hz and the sampling time is 0.5*s* and the signal is shown in Figure 1(d), the impact component is completely submerged in noise and harmonic signal, it is unable to distinguish the impact signal.

Then morphological component analysis was used for the synthetic signal. In MCA. the number of iterations was set as 100, select discrete cosine transform (DCT) dictionary to characterize the harmonic components and using the dirac dictionary to symbolic the harmonic components. The decomposition results were shown in Figure 2. From the results, it can be seen that harmonic components and impact components can be accurately restored by the MCA from synthetic signal. This proves that MCA has good decomposition ability for mixed signals and can separate the required components according to the corresponding dictionary.

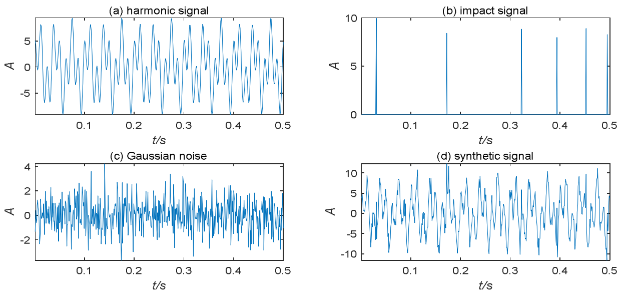

Figure 1. Simulation signals

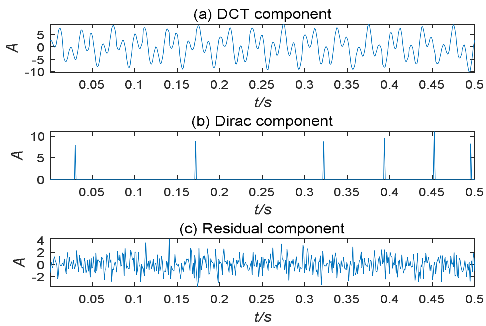

Figure 2. Synthetic signal decomposition by MCA

4. APPLACATION

4. 1. Technological Process of the Proposed Method The original vibration signal of the automaton contains a large amount of interference signals and background noise, which makes it difficult to extract fault characteristics directly. Motived by the advantages of MCA in separating the impact components, a new feature extracting method is proposed for automaton fault diagnosis. The flowchart of this method is depicted in Figure 3.

4. 2. Experimental Platform The proposed method was validated on an automaton experimental platform, the test platform consists of three parts: the automaton, the pneumatic control device and data collection system, as shown in Figure 4. In the experimental platform, the automaton is the main device, the sensor installation position is shown in Figure 4(a). It is a piezoelectric acceleration sensor, the type is CA-YD-193. Pneumatic device keeps the automaton working continuously, and the data acquisition system is used to collect the vibration acceleration signal along the axial direction of automaton, the sampling frequency is 10KHz and the sampling number is 1200 points.

4. 3 Fault Settings In the actual working process of the automaton, due to the influence of high temperature, high pressure, strong ablation and high rate of fire conditions, the automaton's locking block is prone to produce wear and pitting fault; the spring in the ballistic mechanism is prone to fatigue failure. The wear and pitting faults may cause the automaton latch could not reach the correct position, the fatigue failure may cause the breech bolt could not reach the normal re-entry position in time and reducing the shooting speed. Figure 5 is the process of fault experiment. The settings of the three faults are shown in Figures 6(a), 6(b) and 6(c). In the experiment, the data of normal state and 3 fault states are collected and 20 groups of data were collected for each condition, among these 20 groups data, 10 groups were used for training and the remaining were used for testing. These details are given in Table 1.

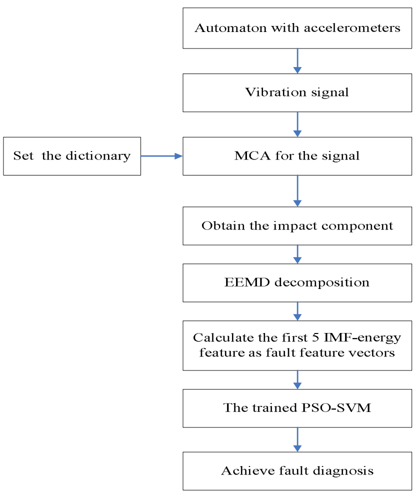

Figure 3. Flow chart of the of the proposed method

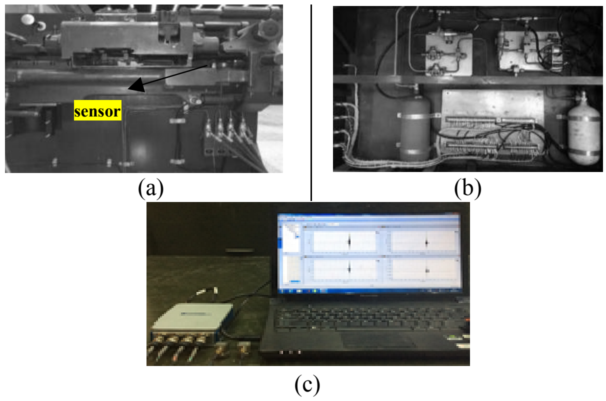

Figure 4. Automaton experimental platform. (a) automaton. (b) pneumatic control device. (c)data collection system

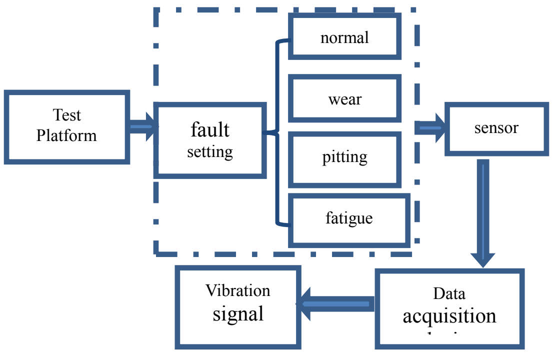

Figure 5. The flow chart of automaton typical fault experiments

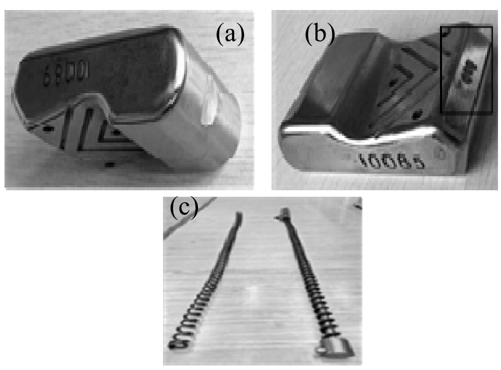

Figure 6. Automaton fault setting (a) wear (b)pitting (c)spring fatigue

TABLE 1. The detailed arrangements of the experimental data sets for classification

Conditions	Class label	training data	testing data
healthy	1	10	10
wear	2	10	10
pitting	3	10	10
fatigue	4	10	10

4. 4. Morphological Component Analysis (MCA) for Automaton Vibration Signal In the experiment, the original vibration signal under four different conditions were shown in Figure 7. When the fault occurs in the automaton, the impact component in the vibration signal changes and the shock component contains most of the fault characteristics, so analyzing the impact components is the key to fault feature extraction [2-4]. However, the complexity of the working conditions of the automaton makes it difficult to extract the impact components from vibration signals which contain unknown interference components and background noise. We used MCA to separate the impact components from the original vibration signals. Before the decomposition, it needs to choose a dictionary, here using undecimated discrete wavelet transform (UDWT) as the analysis dictionary to match the impact components in the vibration signal, the wavelet function is symlet 8, semi-soft threshold was chosen as threshold function and the number of iterations was set to 100. Then perform the MCA under MATLAB and the separated impact component is show in Figure 8.

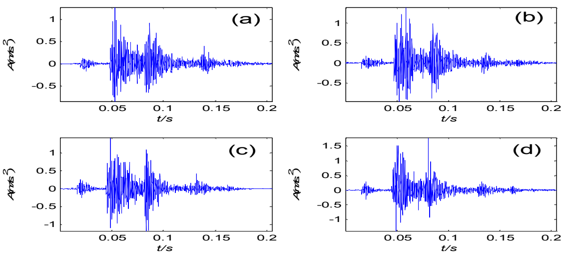

Figure 7. The original vibration signals. (a) normal condition. (b)wear fault. (c) pitting fault. (d) spring fatigue

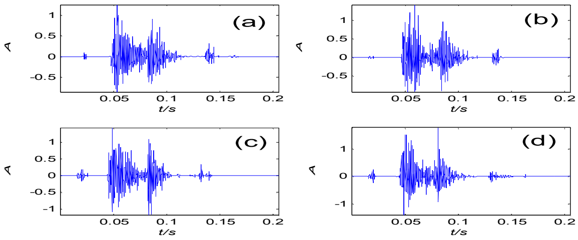

Figure 8. The separated impact component by MCA from original signal.

In order to quantitatively analyze the separation effect of the impact component, here we defined the signal-to-noise ratio between the impact component and the original signal. The calculation process is as follows:

$$R_{sn} = 10 \lg \left\{ \sum_{n=0}^{N-1} S_n^{\,2} \Big/ \left[\sum_{n=0}^{N-1} \left(S_n - \overline{S}_n \right)^2 \right] \right\} \tag{12}$$

where S_n is the original signal, $\overline{S}_n$ is the impact component obtained by MCA decomposition, and N is the number of sampling points. A high value of R_{sn} indicates that the effect of noise reduction is better.

E_r is the energy ratio of the impact component to the original signal. E_r was defined as follows:

$$\begin{aligned} E_0 &= \sum_{i=1}^{m} |x(t)|^2 \\ E_r &= E_{im} / E_0 \end{aligned} \tag{13}$$

E_0 is the energy of original signal and E_{im} is the impact component energy; The magnitude of E_r reflects the proximity of the impact component to the original signal. it is expected to obtain a larger E_r in order to have a better decomposition result.

Calculate the R_{sn} and E_r for the vibration signals, the result are shown in Table 2. From the result, we can find the decomposed impact signals not only have a high signal-to-noise ratio, but also contain most energy of the original vibration signal. This shows that the MCA method has good noise reduction and impact component extraction capabilities.

TABLE 2. The result of R_{sn} and E_r and in four conditions

Fault type		Normal		Wear		Pitting		Fatigue	
		$R_{sn}(dB)$	$E_r(\%)$	$R_{sn}(dB)$	E_r (%)	$R_{sn}(dB)$	$E_r(\%)$	$R_{sn}(dB)$	$E_r(\%)$
Signal number	1	11.3	87.62	11.5	89.10	12.4	90.52	11.7	89.86
	2	13.4	92.74	11.5	89.10	8.3	82.68	11.3	89.08
	3	11.4	87.94	10.0	88.45	8.5	85.97	12.4	90.10

4. 5. EEMD energy feature Extraction The impact signals obtained from MCA were decomposed by EEMD, the intrinsic mode functions（IMFs）1-11 and residual component (r) are displayed in Figure 9. Since the first five IMFs are highly correlated with the original signal, these components are selected to calculate the energy feature using Equation (13) as the fault feature vectors. Part of the results are shown in Table 3.

4. 6. Fault Identification The fault feature vectors in four states were input into the SVM for identification, and the SVM parameters (penalty parameter C, kernel function parameter g) are optimized using the particle swarm optimization (PSO) algorithm [14]. The optimal parameters are C=1.145, g=0.2703, and the recognition results are as shown in Figure 10. As indicated in Figure 10, it can be observed that the automaton fault diagnosis model can recognize the fault types effectively. In order to verify the advantages of the method proposed in this paper, compare it with EEMD feature extraction method, the comparison results in Table 4 show that the proposed method's fault correct recognition rate is superior to the direct feature extraction method.

5. CONCLUSION

In this study, a new automaton feature extraction algorithm has been proposed, this approach is a combination of MCA, EEMD and energy feature method.

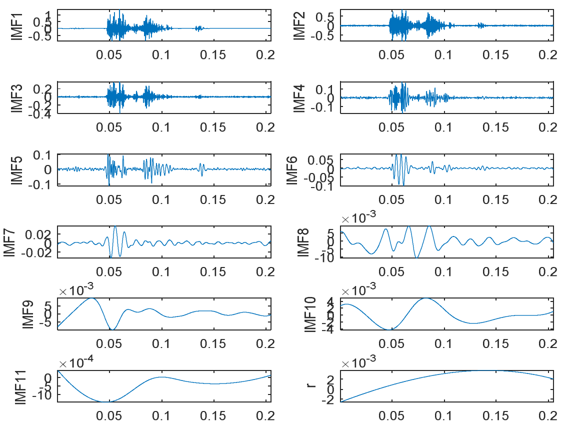

Figure 9. The results based on EEMD for wear fault

TABLE 3. The energy feature of the first five IMFs

IMF-energy	IMF1	IMF2	IMF3	IMF4	IMF5
normal	0.5077	0.3895	0.0599	0.0256	0.0173
	0.5032	0.3841	0.0633	0.0329	0.0164
wear	0.4807	0.4372	0.0563	0.0183	0.0075
	0.4764	0.4389	0.0560	0.0204	0.0083
pitting	0.4970	0.3723	0.0897	0.0281	0.0128
	0.5015	0.3660	0.0870	0.0299	0.0156
fatigue	0.5485	0.4355	0.0733	0.0269	0.0157
	0.5506	0.4024	0.0614	0.0302	0.0054

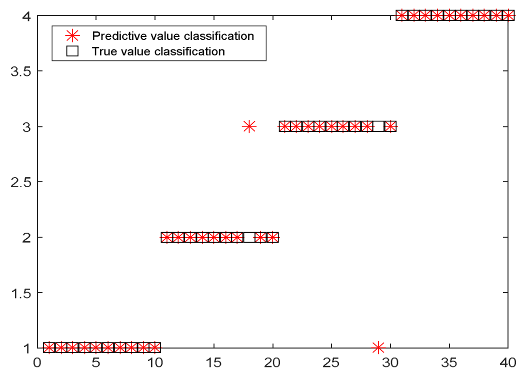

Figure 10. The diagnosis result of test data

TABLE 4. The recognition result comparison of EEMD and MCA-EEMD method

Conditions	EEMD		MCA-EEMD	
	Correct	Accuracy (%)	Correct	Accuracy (%)
normal	9	82.5	10	95
wear	8		9	
pitting	7		9	
fatigue	9		10	

The effectiveness of the MCA approach is investigated and its advantages in fault feature extraction are validated using both the simulated and experiment signals. It has a good ability to remove the noise and extract the effective impact components from complex signal. Experimental results demonstrate that the proposed method can successfully identify multiple types of faults on automaton.

6. ACKNOWLEDGEMENTS

This research is supported by the Hebei Province Science Foundation (No. E2016506003).

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Paper history:
Received January 08 2019
Received in revised form 14 March 2019
Accepted 02 May 2019

Keywords:
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چکیده

در تشخیص خطا اتوماتیک، سیگنال ارتعاش ارائه غیر ثابت و غیر دوره ای است، که باعث می شود ویژگی های گسل را استخراج کند. برای حل این مشکل، یک روش تشخیص خطای اتوماتیک براساس تجزیه و تحلیل جزء مورفولوژیکی (MCA) و تجزیه حالت تجربی (EEMD) پیشنهاد شد. بر اساس مزایای روش تجزیه و تحلیل مؤلفه های مورفولوژیکی در جداسازی سیگنال، با استفاده از اختلاف مورفولوژیکی مولفه ها در سیگنال ارتعاش اتوماتیک، لغت نامه های نزولی مختلف برای جداسازی قطعات، حذف اجزاء نویز و استخراج جزء مشخصه خطای گشت ساخته شد. اجزای تاثیر استخراج شده توسط EEMD تجزیه می شوند و ویژگی انرژی هر یک از اجزای IMF به عنوان ویژگی های خطا محاسبه می شود و سپس ویژگی های خطا را به پشتیبانی از ماشین بردار (SVM) و شناسایی خطاها اختصاص می دهد. از طریق مثال شبیه سازی ساخت و آزمون معمول شبیه سازی خطای دستگاه اتوماتیک، نشان داد که روش تجزیه و تحلیل مورفولوژیکی جزء بهتر از کاهش نویز و اثر جداسازی سیگنال است. در مقایسه با روش EEMD سنتی، روش استخراج ویژگی بر اساس MCA-EEMD می تواند انواع گسل های اتوماتیک را به طور موثر تر تشخیص دهد.

***doi**: 10.5829/ije.2019.32.06c.12*