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Fault Diagnosis of Automaton Based on EMD and Close Degree

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Abstract: Targeting the non-stationary characteristics of short and transient impulse vibration signals of high speed automaton, a new method based on empirical mode decomposition (EMD) and close degree to diagnose fault for high speed automaton is proposed in this paper. Firstly, original acceleration vibration signals are decomposed into a finite number of stationary intrinsic mode functions (IMFs), and then the EMD energy of each IMF is calculated. The correlation analysis is applied and the results show that the first three IMFs contained the most dominant fault information; therefore, the energy feature extracted from the first three IMFs that could serve as a feature vector for fault patterns recognition of automaton. Finally close degree evaluation method was used to diagnose the automaton fault. The experimental results indicate that the proposed approach put forward in this paper can effectively identify automaton fault patterns and it has a great application potential in condition monitoring and fault diagnosis of automaton. *Copyright © 2013 IFSA.*

Keywords: High-speed automaton, Empirical mode decomposition (EMD), Correlation analysis, Close degree evaluation method, Fault diagnosis.

1. Introduction

Automaton is the core institution of the gun to complete automatic fire, whose performance state will directly affects the gun's stability and reliability. Because the difficulties of testing impulse response signal when the high speed automaton is launching and the limitations on the validity of data processing technology, until now the fault diagnosis methods and the research on the reliability of institutions operating for automaton are very little. The mainly method is only the reliability theory research and simulation based on fault tree analysis [1]. Therefore, in the manufacture and experiment, it is necessary to carry out condition monitoring, judge and evaluate the running status or wear condition, so as to identify the fault and take effectual measures to prevent it, thereby to improve the lifetime of automaton.

With the vile working condition, the motion process of automaton is not a periodic process, the direct action time of each component during launching process is very short, and the vibration response signal is generated by the collision between components, therefore the signal is a short, transient and non-stationary signal. Recently, a new signal analysis method, namely empirical mode decomposition (EMD) developed by Huang et al., has been based on the local characteristic time scale of the signal and can decompose the complicated signal into a number of intrinsic mode functions (IMFs) [2]. By analyzing each IMF component that involves the local characteristic of the signal, the characteristic

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information of the original signal could be extracted more accurately and effectively. In addition, the frequency components involved in each IMF not only relates to sampling frequency but also changes with the signal itself; therefore, therefore, EMD is a self-adaptive signal processing method that can be applied to nonlinear and non-stationary signal process perfectly, and which has overcome the limitation of the traditional signal process method and has high SNR as well [3-6].

In this paper, the fault diagnosis method for automaton based on EMD and close degree was proposed. First, the acceleration vibration signal was decomposed by EMD and a number of IMFs are obtained; then using the correlation analysis, the first three IMFs were extracted as a feature vector, and fuzzy clustering method was used to further validate the rationality of the feature vector; finally the close degree state evaluation criteria was applied to identify the strange samples. The diagnosis result indicates that the proposed method in feature extraction and fault diagnosis for automaton is effective.

2. EMD Method [7]

EMD method develops from the simple assumption that any signal consists of different simple intrinsic modes of oscillations. Each linear or non-linear mode will have the same number of extrema and zero-crossings. There is only one extremum between successive zero-crossings. Each mode should be independent of the others. In this way, each signal could be decomposed into a number of IMFs, each of which must satisfy the following two conditions [2]:

1) The number of extreme points and zero crossings of the original signal must be equal or at most differ by one.

2) At any point, the mean value of the envelope defined by local maxima and by the local minima is zero.

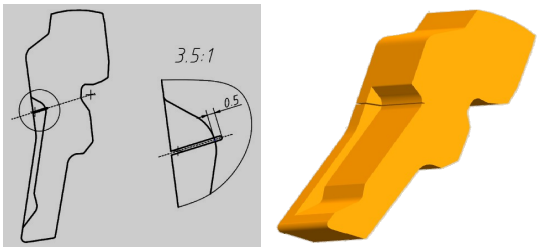
By EMD, the signal was decomposed into a number of IMFs $c_1(t), c_2(t), c_3(t), \cdots, c_n(t)$ and a residue component $r_n(t)$, which is the mean trend of $x(t)$ or a constant. Each IMF component contains a different signal from high to low frequencies ingredients. The decomposition process can be stopped when $r_n(t)$ becomes a monotonic function from which no more IMFs can be extracted. The IMFs $c_1(t), c_2(t), c_3(t), \cdots, c_n(t)$ include different frequency bands ranging from high to low. The frequency components contained in each frequency band are different and they change with the variation of signal x(t), while $r_n(t)$ represents the central tendency of signal $x(t)$.

The decomposition process will be stopped when $r_n(t)$ becomes a monotonic function from which no more IMFs can be extracted. So the original signal can be expressed as:

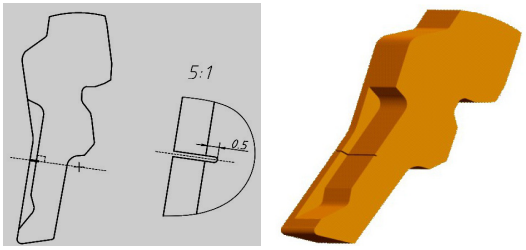
$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t) \quad (1)$$

3. Experimental Analysis

During the manufacturing process of the gun, the fault is mostly crack fault on the locking piece, so according to the experience and the experimental stress analysis, two faults were set in this experiment. The fault positions are shown in Fig. 1.



(a) Crack location distribution of the fault 1.



b) Crack location distribution of the fault 2.

Fig. 1. Fault location.

In the experiment, two measuring points were respectively set in the top of gun tail and the left side of gun box, where the acceleration sensors of model 44987 and model 44999 were respectively installed, and the sampling frequency is 51.2 kHz, the locations of measuring points are shown in Fig. 2. The launching pattern was three bursts firing. By repeatedly shooting, many vibration acceleration signals of automaton in normal and two fault states were obtained. In this paper, we mainly discuss and research the signals generated in measuring point 1.

3.1. Signal Analysis

Considering the X-axis direction is the reciprocation direction of the automaton, and the shock and vibration energy is relatively large in this

direction, so the signal generated in this direction was analyzed. Fig. 3 shows the vibration acceleration signal of the X-axis direction in the normal state.

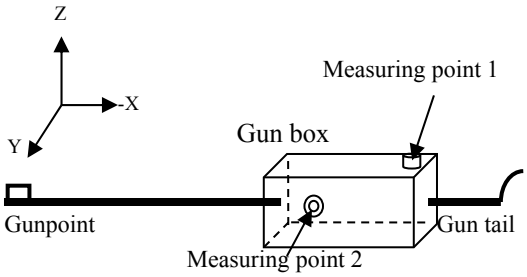


Fig. 2. Location of measuring points.

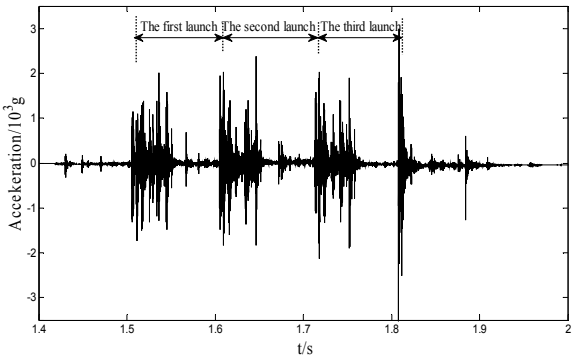


Fig. 3. Vibration acceleration signal of X-axis direction in normal state.

From Fig. 3, we can see that the vibration response signal has a strong impact, but it is relatively stable, and it has certain regularity. According to the motion rules of each component, each shot process can be distinguish from the time domain diagram, so three bursts shot can be regarded as three single shot. In the experiment, the automaton's faults were set in the locking piece, according to the movement rules of automaton, the vibration signals generated in the latching stage includes the free travel of the locking piece were extracted for analysis. The signal generated in the latching stage is shown in Fig. 4.

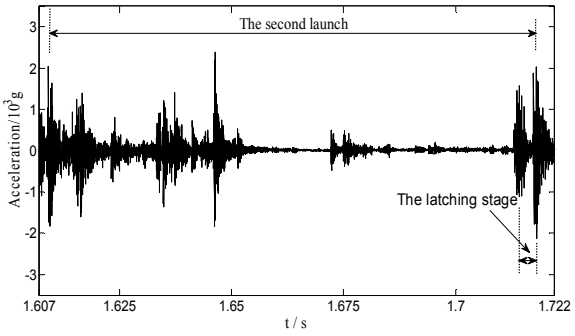


Fig. 4. Vibration signal in the latching stage.

3.2. Signal Processing by EMD

In this paper, vibration signals generated in three working conditions during the latching process of the automaton were decomposed by EMD and a number of IMFs were extracted. The decomposition results by EMD in three conditions were shown in Fig. 5. From Fig. 5, it can be seen that the wave shapes and amplitude of each IMF component between any two working conditions are obviously different, which can basically reflect the work condition and the fault pattern of the automaton. But it is not enough if we distinguish the work condition and identify the fault pattern only according to the EMD, further analysis should be desirable.

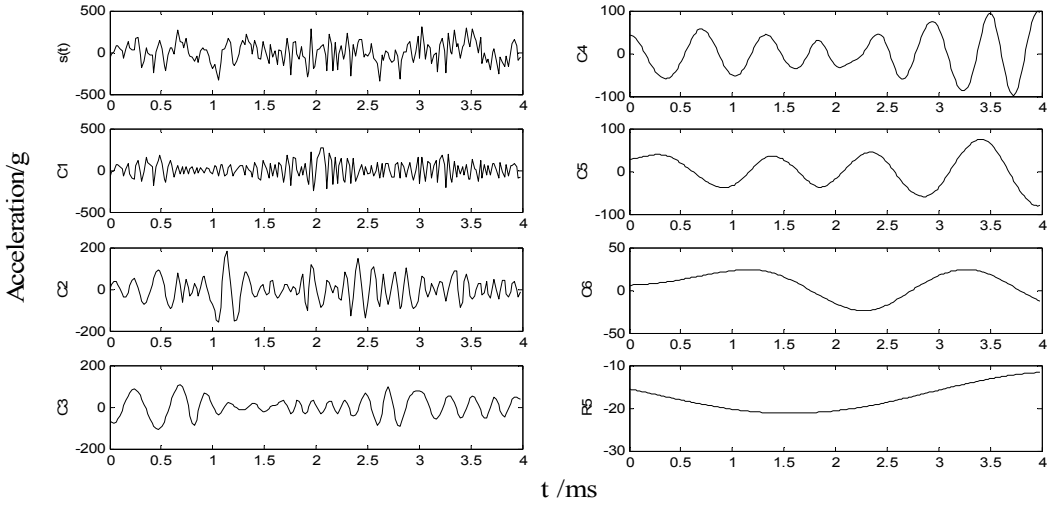


Fig. 5 (a). EMD of three conditions: fault 1.

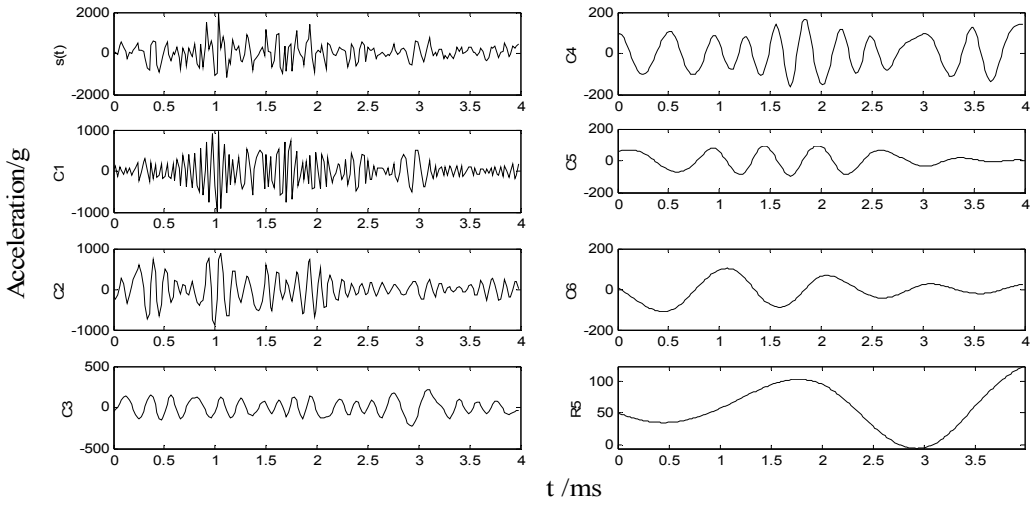


Fig. 5 (b). EMD of three conditions: fault 2.

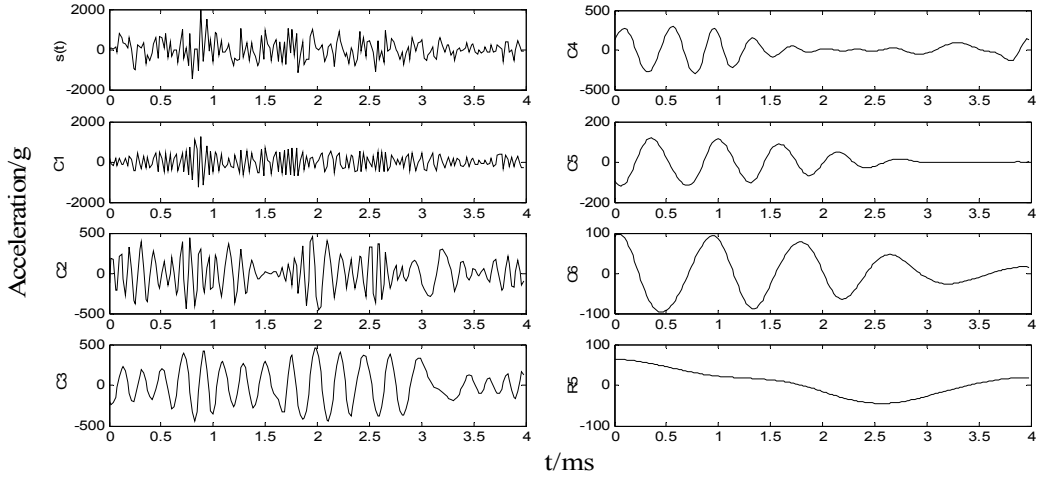


Fig. 5 (c). EMD of three conditions: normal.

4. Feature Extraction and Fault Diagnosis

4.1. Feature Extraction

According to the above method, the vibration signals of three working conditions of the automaton were decomposed, then six basic IMFs were obtained and the corresponding energy were calculated in Table 1. Since modal aliasing and false weight may be produced inevitably by EMD, so the correlation analysis is adopted to choose the main IMFs that include the most dominant fault information. Cross-Correlation coefficient is a parameter that characterizes a degree of correlation between the sequences, the bigger the coefficient is, the greater the relationship degree will be. Therefore the coefficient can be used to determine the degree of each IMF contains the information of the original signal. So the correlation coefficient between each IMF and corresponding original signal was calculated, and the results were shown in Table 2. As can be seen from Table 2, the correlation coefficient between the first three components and the corresponding original signal are commonly greater than 0.1, and the correlation coefficients are also greater than the others, it can be considered that the first three components can best reflect the characteristics of the original signal.

From Table 1, it also can be seen that the energy value of the first three components of fault 1 and fault 2 are generally small compared to the normal state, in which each energy value of fault 1 are smaller than the other two states. In addition, we can see that the energy value of each IMF components in the same condition has a certain similarity, and there are some differences between any two different working conditions. Therefore the first three components are chosen as the fault feature vector for the automaton's fault diagnosis is reasonable. To further validate the effectiveness of the feature extraction method, the fuzzy clustering method is adopted. The cluster analysis results are shown in Table 3.

Table 3 shows, the clustering efficiency of the first three IMFs are taken as the feature vector is better than all six components as the feature vector, the former classification coefficients are 0.8365, which is greater than the latter 0.7029. It indicates that the former is more accurate. Thus the first three IMFs are selected as feature vector for the automaton fault diagnosis is further validated effectively.

Table 1. The energy values of each IMF of three conditions by EMD (Unit: 10 ^ 3g2).

Samples		E1	E2	E3	E4	E5	E6
Fault 1	x_1	2.0501	1.6505	1.4681	1.3976	1.0870	1.2014
	x_2	1.9390	1.5282	1.2340	1.5556	1.3040	1.1146
	x_3	1.8130	1.4508	1.2840	1.0137	1.1627	0.8988
Fault 2	x_4	2.9760	2.8021	1.7298	1.6632	1.1889	1.2235
	x_5	3.4757	2.4622	2.2708	1.7702	1.3082	1.5917
	x_6	3.0004	2.7337	1.9183	1.4717	1.0932	1.5155
Normal	x_7	4.1351	3.6279	2.6545	1.6247	1.4343	1.2073
	x_8	4.0409	3.0847	2.8199	1.5234	1.5122	0.9324
	x_9	5.0807	3.4403	2.7077	2.1499	1.5999	1.1303

Table 2. The correlation coefficients of each IMF compared with corresponding original signal

Samples		R1	R2	R3	R4	R5	R6
Fault 1	x_1	0.6468	0.4486	0.3168	0.2128	0.2023	0.1270
	x_2	0.6620	0.4369	0.2427	0.3429	0.1706	0.1604
	x_3	0.6764	0.3263	0.2482	0.2267	0.1461	0.0946
Fault 2	x_4	0.6873	0.6606	0.1504	0.1693	0.0962	0.0934
	x_5	0.7508	0.4633	0.3169	0.2752	0.1945	0.0290
	x_6	0.7443	0.5486	0.2668	0.1673	0.0608	0.0272
Normal	x_7	0.8143	0.3879	0.3187	0.1813	0.1318	0.0246
	x_8	0.8095	0.4346	0.2012	0.1016	0.0435	0.0375
	x_9	0.7784	0.4495	0.3242	0.2465	0.1779	0.0935

Table 3. Clustering results.

Numbers of IMF	Class coefficient	Result
First three IMFs	0.8365	Three classes ($\{x_1, x_2, x_3\}$, $\{x_4, x_5, x_6\}$, $\{x_7, x_8, x_9\}$)
Six IMFs	0.7029	Three classes ($\{x_1, x_2, x_3\}$, $\{x_4, x_5, x_6\}$, $\{x_7, x_8, x_9\}$)

4.2. Close Degree Evaluation and Fault Diagnosis

4.2.1. Close Degree Model [8]

Suppose $W_1, W_2, \cdots, W_n$ are n types of reference state sets of the evaluation system, which is diagnosed by experts, each type of state set corresponds to an evaluation result. If W_i is the i^{th} type of reference state set, A is the state to be evaluated, $N(A, W_i)$ is used as a close degree between A and W_i. If $N(A, W_k) = \max_{1 \le i \le n} \{N(A, W_i)\}$, A is assessed to be the k^{th} type of state.

Conceptually, if the smaller the distance between two state spaces is, the greater the close degree between the two states will be. In this paper, the Euclidean distance formula is applied to describe the close degree:

Assume that the space distance between the state to be evaluated and the i^{th} type of reference state is $d_i = (\sum_{j=1}^{k} (a_j - w_{ij})^2)^{1/2}$, where w_{ij} is the i^{th} evaluation index of the i^{th} type of reference state; a_j is the i^{th} index value of the state to be identified. So the sum of space distance between the state to be identified and all reference states is $D = \sum_{i=1}^{n} d_i$, then the close degree is defined as:

$$N(A, W_i) = 1 - d_i / D \tag{2}$$

It can be calculated by the formula (1) that $N \in [0, 1]$, when the state to be identified fully coincides with a reference state, the corresponding distance d_i is 0, and the close degree N is 1.

4.2.2. Fault Diagnosis Based on IMF Close Degree

According to the above fault feature extraction method, the energy band of the first three IMFs of three different working conditions are obtained as three reference states and they are expressed in Table 4. Suppose (L_{ij}, M_{ij}) is the energy band of the ith type of reference state, where L_{ij}, M_{ij} are respectively the up and low energy threshold of the i^{th} component of the ith type of reference state, C_j expresses the i^{th} component of the test sample, $j = 1,2,3$, so the energy band distance of the i^{th} component between the test sample and the ith type of reference state can be defined as:

$$d_{ij} = ((L_{ij} - C_j)^2 + (M_{ij} - C_j)^2)^{1/2} \quad (3)$$

The total distance with the i^{th} type of state is:

$$D_i = (d_{i1}^{\ 2} + d_{i2}^{\ 2} + d_{i3}^{\ 2})^{1/2} \quad (4)$$

Corresponding close degree is:

$$N(A, W_i) = 1 - D_i / \sum_{i=1}^{3} D_i \quad (5)$$

Table 4. The energy bands of three types of reference state.

Working conditions	IMF1	IMF 2	IMF3
Fault 1	1.8130~2.0501	1.4508~1.6505	1.2340~1.4681
Fault 2	2.9760~3.4757	2.4622~2.8021	1.7298~2.2708
Normal	4.0409~5.0807	3.0847~3.6279	2.6545~2.8199

In the paper, two groups of strange samples are set to be tested. Firstly, two samples are respectively decomposed by EMD and the features are obtained by the above method. The feature vectors of sample 1 is (1.5808, 1.1558, 1.1390) and the sample 2 is (3.2502, 2.6551, 2.2122). According to the equation (3), (4) and (5), the close degrees between two test groups and three reference states are calculated and shown in Table 5.

Table 5. The close degrees compared with the different reference states.

	With the normal state	With the fault 1	With the fault 2
Test sample 1	0.4245	0.9151	0.6603
Test sample 2	0.5869	0.5257	0.8874

It can be seen from Table 5, for the test sample 1, the close degree is maximum compared with fault 1, so the test sample 1 can be identified as fault 1 pattern; similarly, test sample 2 can be diagnosed as fault 2. The testing results consistent with the actual experimental results, which indicate that the proposed method can accurately identify the patterns of fault and it can be used as a new reference method for fault diagnosis of automaton.

5. Conclusions

According to the non-stationary characteristics of automaton faulty signals, a fault diagnosis method based on EMD and close degree is put forward in this paper. First, EMD was utilized to preprocess different types of vibration signals. Then by the correlation analysis, it shows that the relativities between the first three IMFs and the original signal are relatively large, so the first three IMFs were extracted as the feature vector is reasonable. And the use of fuzzy clustering method further validate that choosing the first three IMFs as a feature vector is better than choosing all IMFs. Finally the close degree condition identification method was used on the preprocessed data in order to determine the work condition of automaton. The testing results show that the test samples can be correctly and effectively identified. The experimental results above show that the proposed EMD can be applied to nonlinear and non-stationary processes perfectly and can accurately extract the faulty information of automaton. The combination of EMD with close degree successfully identified the work conditions and fault patterns of automaton and provided a useful tool for faults diagnosis in automaton.

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