

Application of wavelet entropy and grey relational analysis in fault diagnosis of hydraulic system of engineering machinery

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Abstract. The working environment of engineering machinery is complex. The signal of the equipment in operation is characterized by non-stationary and complex variability. In this paper, the wavelet transform is used to extract the non-stationary fault signals of the hydraulic system of the equipment. At the same time, a fault classification method based on the multi wavelet entropy feature extraction is proposed with the information entropy. The fault features are extracted quickly and accurately. The grey correlation analysis method is used to identify the fault, and the remote fault is set up. Diagnosis platform. The results show that the method can improve the support and accuracy of the fault diagnosis, and provides a feasible new method for the fault diagnosis of the engineering machinery.

1. Introduction

In recent years, the frequency and complexity of Engineering machinery have increased, and the current loader, excavator, etc., in addition to the traditional mechanical system and hydraulic system function more perfect, the system also increased the vehicle control system, GPS/BDS and other intelligent equipment. Engineering machinery generally used in the outdoor, wind, dust, sunlight and the surrounding environment, resulting in different degrees of failure [1-5]. In order to ensure that the Engineering machinery in good operation state, from 1960s, the developed countries such as the United States, Japan and other developed countries have carried out the research of mechanical system fault diagnosis. In 1980s, China some colleges and universities have also carried out the research of fault diagnosis. So far, the Xi'an Jiao Tong University has successfully applied the wavelet signal processing technology to fault diagnosis [6-8]. Recently, some scholars have adopted the hologram spectrum technology to improve the fault recognition rate. The current fault diagnosis of engineering machinery is mainly based on the fault diagnosis method based on the feature extraction of the equipment. The signal processing method is used to locate and analyze the non stationary time-varying signal at the same time in the frequency domain and time domain, and the shape of the wavelet transform window is variable[9-15]. In order to facilitate the local analysis of signals, the various wavelet entropy defined on this basis is the product of the combination of wavelet transform and the principle of information entropy. It combines the unique advantages of the wavelet transform in dealing with irregular abnormal signals and the statistical characteristics of the information entropy on the complexity of the signal. The characterization of obstacle information has unique advantages. It has been applied in some fields, such as machinery and power fault diagnosis.



The method of grey relational analysis is a measure of the correlation between two systems or two factors, which can describe the relative changes between factors in the process of system development. Because of the advantages of "low sample demand and small amount of calculation", grey relational analysis has been widely used in mechanical fault diagnosis which is difficult to obtain in a large number of fault samples, and has achieved good results [16-18].

In this paper, the feature of fault signal is extracted by multi wavelet entropy, and a fault diagnosis method based on the grey correlation analysis of signal wavelet entropy is proposed based on the grey correlation analysis theory. A remote fault diagnosis platform for excavator is set up. The platform is simple and the field test data verifies the effectiveness of the method. It has a very broad application prospect.

2. Random Signal and Wavelet Entropy

Initially entropy means that the heat energy divided by the temperature is the amount of heat that is converted to work. Later entropy is used to represent functions that describe and characterize the uncertainty of the system. It can provide useful information in the latent dynamic process of signals[19-21]. In wavelet transform, a single frequency periodic signal, except for the wavelet scale containing the typical signal frequency, the other wavelet coefficients are almost zero. For this special scale, the wavelet coefficient will be close to 1, when the entropy of the signal will be close to 0 or a very small value. On the contrary, a completely disordered random signal has a wavelet coefficient on all frequency bands, and there is no obvious difference in the size of the coefficients. In this case, the entropy of the signal will be close to 1. Generally, the more chaotic the probability distribution of the signal is, the greater the entropy value is, the entropy of the signal of the random signal reflects the uniformity of the probability distribution.. The coefficient matrix of the wavelet transform is processed into a probability distribution sequence. The calculated entropy can reflect the sparsest of the coefficient matrix, that is, the order degree of the probability distribution of the signal, which is called the wavelet entropy.

2.1. Energy Entropy of Wavelet Signal

The wavelet energy entropy is the statistical analysis of the energy distribution of the signal collected by the analyzed system in each frequency band. Usually, the signal energy is divided by the scale coefficient of the wavelet transform, and the distribution of the signal energy in the frequency domain is reflected by a entropy value.

Let $E = E_1, E_2, \dots, E_n$ be the wavelet energy spectrum of signal $x(t)$ at m scale. E can form a division of the energy of random signals in the scale domain. In this paper, an extension is made in this paper. The characteristics of orthogonal wavelet transform show that the total power E_j in a time window ($\omega \in E$) is equal to the sum of the power of each component. Set, $p_j = \frac{E_j}{E}$ the $\sum_j p_j = 1$, the corresponding wavelet energy spectrum entropy W_{EE} is defined

$$W_{EE} = -\sum_j p_j \log p_j \quad (1)$$

With the sliding of wavelet windows, the law of wavelet energy entropy changing with time can be obtained.

2.2. Wavelet Singular Entropy

The basic modal characteristics of the matrix can be extracted successfully by the singular value decomposition theory. The characteristics of the wavelet transform coefficient matrix of the signal can be extracted by the SVD theory to reflect the time frequency distribution characteristics of the analyzed signal.

The hypothetical signal is in J ($j=1, 2 \dots M$) wavelet decomposition at the scale, then the decomposition results on the M scale can be a matrix $D_j(n)$. According to the singular value decomposition theory of signal processing, there exists a $m \times l$ dimensional matrix U and a $l \times n$ dimensional matrix V and a $l \times l$ dimensional matrix Λ for an $m \times n$ matrix D , so that the matrix D can be decomposed into:

$$D_{m \times n} = U_{m \times l} \Lambda_{l \times l} V_{l \times n}^T \quad (2)$$

In the formula, the diagonal elements of diagonal matrix ($i=1, 2 \dots l$) is nonnegative and is arranged in descending order, that is $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_l \geq 0$ the singular value of the result matrix of the diagonal elements of $D_{m \times n}$. The singular decomposition theory of the reference signal shows that when the signal has no noise or has a high signal to noise ratio, the singular value on the main diagonal line is only a few zero. The singular value of the signal wavelet decomposition result matrix satisfies the similar law at the same time, and the frequency component of the signal is less, the singular value of the result after the signal is decomposed. The less the number is not zero. In order to quantitatively describe the frequency components and the distribution of characteristics of random signals, the wavelet singular entropy is defined as:

$$W_{SEK} = \sum_i^k \Delta p_i \quad (3)$$

In the formula, the j order incremental wavelet singular entropy.

$$\Delta p_i = - \left[\frac{\lambda_i}{\sum_{j=1}^l \lambda_j} \right] \log \left[\frac{\lambda_i}{\sum_{j=1}^l \lambda_j} \right] \quad (4)$$

The singular value decomposition of the wavelet transform result matrix of the signal is to map the associated wavelet space to the linearly independent feature space. The wavelet singular entropy can quantification ally distinguish the signals with different time frequency distribution, and the more complex and uncertain the signals are, the greater the singular entropy value of the quantized wavelet is. The fault signal of the hydraulic system is rich in high frequency transient components, and the complexity of the time frequency space is very complex after the change of the signal The fault degree can be detected and quantified by the wavelet singular entropy.

2.3. Wave Time Frequency Entropy

The wavelet time frequency entropy is the wavelet transform coefficient matrix of the analyzed random signal, and the energy statistics analysis is carried out from the angle of time and frequency respectively, and then 2 related entropy values are obtained. One of them has frequency ergodicity, reflects the frequency complexity of the analyzed signal, and the other has time ergodicity, which can reflect the signal in the Time distribution on each frequency band.

Based on the scale I , wavelet coefficients $D = \{d(k), k = 1, 2, \dots, N\}$, A sliding window is defined on the wavelet coefficients, The width of the wavelet window $w \in N$, slippage factor $\delta \in N$, Sliding window is:

$$W(m; w, \delta) = \{d(k), k = 1 + m\delta, 2 + m\delta, \dots, w + m\delta\} \quad (5)$$

The sliding window can be divided into L intervals, and the following results can be obtained.

$$W(m; w, \delta) = \bigcup_{l=1}^L Z_l \quad (6)$$

In the formula $\{Z_l = [s_{l-1}, s_l], l = 1, 2, \dots, L\}$ is not intersected from each other.

$$s_0 < s_1 < s_2 < \dots < s_l \quad (7)$$

$$\min[d(k), k = 1 + m\delta, \dots, w + m\delta] \quad (8)$$

$$\max[d(k), k = 1 + m\delta, \dots, w + m\delta] \quad (9)$$

Let $p^m(Z_l)$ be the probability that the wavelet coefficients fall into the interval $d(k) \in W(m; \omega, \delta)$. According to the classical probability theory, Z_l is equal to the ratio of the number of Z_l to the number of the total wavelet coefficients of $W(m; \omega, \delta)$, and can be defined the time entropy of the wavelet in the j scale

$$W_{TE^j}(m) = -\sum p^m(Z_l) \log(p^m(Z_l)) \quad (10)$$

In the formula, $m = 1, 2, \dots, M$ and $M = \frac{(N - \omega)}{\delta} \in N$, The wavelet time entropy can be calculated on each scale accordingly $W_{TE^j}(m), m = 1, 2, \dots, M$, And you can make a change curve $\left\{ \frac{\omega}{2} + m\delta, W_{TE^j}(m) \right\}$ of W_{TE^j} .

Considering the change of current signal or system parameters of the hydraulic power system of the Engineering machinery, the ability of detection and positioning is strong, and the calculation is far below the calculation of the Lyapunov index. Considering that $j = 1$ scale decomposition is susceptible to noise, j is more than 2 in application.

3. Grey Correlation Analysis Method for Fault Feature Vector

Different wavelet entropy can reflect the statistical characteristics of time-frequency distribution of fault signals in hydraulic system of engineering machinery from different angles, so it can provide a basic premise for fault diagnosis. However, because of the uncertainty and incompleteness of the fault information of the hydraulic system of the engineering machinery, especially when the fault information is wrong or lost during the transmission process, not every kind of wavelet entropy can fully reflect the time frequency characteristic of the fault signal. For different types of fault signals, different wavelet entropy algorithms have different characteristics and advantages. If a variety of wavelet entropy is used to analyze the fault signal of the hydraulic system, the characteristics of various wavelet entropy can be used to fuse the advantages of different wavelet entropy into fault diagnosis, and the result of high reliability diagnosis is the key to the fault diagnosis of the engineering machinery. In view of the above reasons, a fault diagnosis model combining wavelet entropy with grey system theory is put forward. In this paper, the grey fault diagnosis of hydraulic power system is unified by wavelet energy entropy, wavelet singular entropy, wavelet time-frequency entropy and other characteristic parameters. In fact, the concept of grey relational degree is to consider the characteristic vectors reflecting the state pattern as the folding line of one dimension space, and to compare the geometric similarity through the correlation degree, thus determining the size of the correlation degree between the modes. The degree of correlation is derived from the average of correlation coefficient. There is a standard model $x_i(k) = \{x_i(1), x_i(2), \dots, x_i(n)\}, i = 1, 2, \dots, N$, i is the type of failure modes commonly used in hydraulic systems; K is the number of sampling points for comparison (the number of feature vectors of a pattern) The mode of being compared (to be checked)

is $x_j(k) = \{x_j(1), x_j(2), \dots, x_j(n)\}$, $i = 1, 2, \dots, N$ In the form j is the category of the checked pattern.

Set x_j to x_i in the point correlation coefficient $\xi_{ij}(k)$, then:

$$\xi_{ij}(k) = \frac{\min_{(j)} \min_{(k)} \Delta_{ij}(k) + \rho \max_{(k)} \Delta_{ij}(k)}{\Delta_{ij}(k) + \rho \max_{(j)} \max_{(k)} \Delta_{ij}(k)} \quad (11)$$

In the formula, $\Delta_{ij}(k)$ is the absolute difference between the K point at $\Delta_{ij}(k)$ and the x_j ; $\min_{(j)} \min_{(k)} \Delta_{ij}(k)$ is the minimum difference of the two level.

$\max_{(j)} \max_{(k)} \Delta_{ij}(k)$ is the maximum difference of level two; ρ is the resolution coefficient, $\rho \in (0, 1]$, When state recognition is made, $\rho = 0.5$. The correlation degree γ_{ij} size reflects the degree of correlation between x_j and x_i :

The system is sorted according to the size of the correlation degree, thus providing the order of the probability of the state mode to be classified as the standard mode. By comparing the state of feature extraction with the state of the failure standard mode, the most frequent failure mode is the operation status of the device. According to the above analysis, the flow chart of wavelet entropy and grey correlation analysis of hydraulic power system is designed as shown in Figure 1. From the results of Table L, it can be seen that the grey fault diagnosis model based on multi small entropy is very effective. In the 5 modes detected, all faults can be correctly identified.

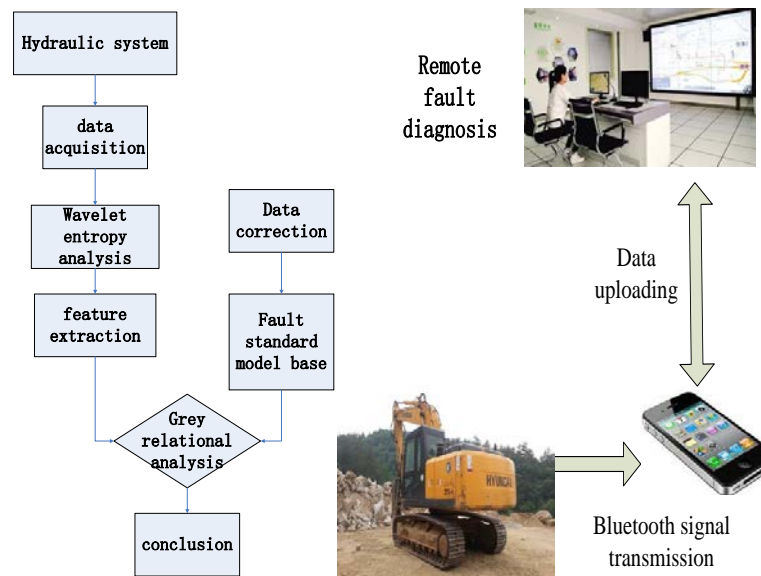


Figure 1. Algorithm and fault diagnosis platform structure

4. Fault Diagnosis and Diagnosis System based on Multi Wavelet Entropy Grey Theory

In order to verify the accuracy of the above scheme and facilitate the field fault diagnosis, a remote fault diagnosis platform is set up on the basis of the existing vehicle fault diagnosis platform of the excavator. The excavator is a typical equipment of the field operation, especially the new model. The realization of the function can not be separated from the hydraulic transmission, and the hydraulic transmission is in the power of power. Transmission also takes into account the optimization of equipment structure. As the hydraulic system occupies a large proportion in the transmission structure, it is necessary to minimize the system failures in routine maintenance. The common faults in the field hydraulic system mainly include the blocking or death of the hydraulic pump, the control failure of the

overflow valve, the pollution of the hydraulic system, the blockage of the pipeline (excessive resistance), the leakage of the system and so on. At present, vehicle borne diagnosis system is mainly used in vehicle diagnosis system. Because the vehicle micro machine is sensitive to dust and humidity, and the vehicle equipment is not suitable for installation of large processing system, the above reasons restrict the function improvement of the fault diagnosis system[22-26]. In view of the above reasons, the signal acquisition module is installed on the hydraulic system. At the same time, in order to facilitate the promotion of the later platform, the mobile APP system can be freely collected. The field data is sent to the mobile phone APP by Bluetooth, and the host computer is uploaded to the remote job monitoring center to carry out the wavelet transform and fault diagnosis. After diagnosis, the result is sent back to the mobile phone for the operator to know the running state of the device. This platform separates complex fault diagnosis and signal acquisition, and the monitoring center can diagnose a number of equipment at the same time, saving the resources convenient for the popularization and use of the equipment. In order to verify the effectiveness of the algorithm and platform, the field experiment was done with the SE130 excavator on mountain. 2 groups of measured pressure signals were sampled in each state, and then the different wavelet entropy was extracted for each state. In each state, 1 groups of signals were selected as stand band the result is shown in Table 1.

Table 1. Analysis of gray correlation degree of signal wavelet entropy

Detection state	Overflow valve failure	Oil stain	System leakage	Pipeline blocking	normal	conclusion
State 1	0.52	0.61	0.58	0.72	0.86	normal
State 2	0.85	0.34	0.53	0.62	0.53	Overflow valve failure
State 3	0.55	0.74	0.63	0.85	0.61	Pipeline blocking
State 4	0.45	0.78	0.53	0.38	0.55	Oil stain
State 5	0.43	0.51	0.68	0.59	0.60	System leakage

According to the results of the obtained Table 1, the failure of the other 4 states except the state 1 is produced. According to the maximum correlation principle, the main fault of the system is fully consistent with the field situation. The experimental results show that the method and the platform are effective.

5. Conclusion

The application principle and advantage of 5 kinds of wavelet entropy measure and its grey theory in fault diagnosis are studied. The scheme based on the theory of multi small gray water gray in the diagnosis of open barrier of hydraulic system is put forward, and the remote fault diagnosis system of engineering machinery is designed. The system is used in the field of the SE130 excavator in the field.

(1) All kinds of small ferry entropy are the organic combination of small transition and information entropy theory, which combines their unique advantages in signal processing. Therefore, it can effectively extract and analyze non-stationary signals and select the characteristic information that can reflect the running state of the equipment, which provides the basis for fault classification.

(2) Combining the soil moisture extraction with the grey correlation degree, the fusion of various small entropy measures by grey theory can reduce the uncertainty of the fault diagnosis results, improve the support rate of the diagnosis results, and thus improve the accuracy of the fault diagnosis.

(3) During the development of the fault diagnosis platform, the field data collection, the wavelet transform, the gray correlation fault diagnosis, the wavelet transform and the fault identification of the fault diagnosis process are given to the remote computer. The efficiency of the system is improved, the cost of the installation is saved and the system is popularized and used.

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