An improved quantitative recurrence analysis using artificial intelligence based image processing applied to sensor measurements

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Abstract: Artificial intelligence has been widely used in reliability analysis for industrial equipment. The gear transmission systems are the most common component in mining machines. A simple fault in the gearbox may break down the mining machine for couple of days, resulting in enormous economic loss. Condition monitoring techniques can prevent unscheduled failures in the gear transmission systems. Although many techniques have been developed for gearbox fault diagnosis, one challenging task that the condition monitoring still faces is how to extract quantitative fault indicators. To this end, this paper proposes an improved quantitative recurrence analysis (IQRA) based on artificial intelligence theory. This new method takes advantages of chaos and fractal properties of the gear transmission system to obtain the recurrence of the system. The characteristics of different gear faults can be observed through the visualization of recurrence. Quantitative parameters can be then calculated from the recurrence plots. Experimental data acquired from a gearbox under variable working conditions was used to evaluate the proposed method. The analysis results demonstrate that the proposed IQRA method is able to effectively quantify different the gear faults.

Keyword: Artificial intelligence; Soft computing; Chaos and bifurcation; Reliability analysis

1. Introduction

Gear transmission systems are the fundamental elements in industry [1], such as coal industry. However, the gearboxes are vulnerable to damages due to hostile operation environments in the coal seams [2]. A simple failure, like a gear crack, may break down the entire coal cutter for several days, leading to numerical maintenance cost. Therefore, it is crucial to perform health monitoring on the gearboxes in coal cutters to prevent any unscheduled failures [3-5].

Due to the fact that the gearbox system is one kind of mechanical system, the dynamic response of the gear system always presents nonlinear characteristics [6]. The artificial intelligence is capable to deal with the system nonlinearity and uncertainty. Chaos theory is among a popular technique in artificial intelligence [7]. The chaotic and fractal properties of a system supplement each other and can be applied to exploring the nonlinear nature in a complex system [8]. This is because in a chaos system there are inherent laws to regular the system behaviors. Specifically, the chaotic and fractal properties in the gear systems can be described by the chaos laws. The chaotic analysis aims to exploit these undetectable essential laws. However, very limited researches have investigated to the chaos laws for reliability analysis, especially for the gear systems in coal cutting machines [9].

One of the challenges in exploiting the chaotic laws is to extract quantitative indicators to characterize the system dynamics. Recently, the chaos theory has been applied in condition monitoring on mechanical systems [10], and the quantitative recurrence analysis (QRA) has been proven to be effective in extraction of quantitative indicators [8-12]. QRA is able to quantify the state change of a system by analyzing the system's chaos characteristics. Particularly, the recurrence plot of QRA is able to visualize the recurrence state of a dynamic system in the phase space [10]. The system health information can be revealed from the topology of the recurrence plot [11]. However, the performance of QRA is subject to noise in the sensor measurements. Very limited researches have investigated effective de-noising strategy in QRA, and to our best knowledge the application of QRA with well-designed de-noiser has not been found in the gearbox diagnostics of coal cutters.

To address the aforementioned challenge, this paper presents an improved quantitative recurrence analysis (IQRA) for condition monitoring of coal cutters. The complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) [13, 14] was firstly adopted to extract the intrinsic vibration mode of the gearbox, discarding the background noise and disturbance in the vibration measurements. Then the chaos properties of the vibration mode were analyzed by QRA to calculate the recurrence parameters, which were used to identify different faults in the gearboxes. Experimental data acquired from a gearbox under variable working conditions was used to evaluate the proposed method. The analysis results demonstrate high performance of the proposed IQRA method, which may provide a new way to contribute to the gearbox fault diagnosis in coal cutters.

2. The improved quantitative recurrence analysis (IQRA)

2.1. A Generic Computational Framework

A generic computational framework of the proposed IQRA is illustrated in Table 1.

Table 1: A generic computational framework

1.	Denoising: Eliminate/reduce the background noise and disturbance in the vibration measurements of the gearbox
1.1	Record the vibration signal of the gearbox using accelerometer.
1.2	Perform CEEMDAN on the vibration measurement to extract the intrinsic fault vibration mode of the gearbox
2.	Quantification: Calculate quantitative indicators from the extracted CEEMDAN mode to detect the gearbox faults
2.1	Reconstruct the phase space of the extracted CEEMDAN mode
2.2	Make the recurrence plot of the CEEMDAN mode in the phase space
2.3	Compute the chaotic parameters as the quantitative fault indicators

2.2. Denoising based on CEEMDAN

The empirical mode decomposition (EMD) is a very powerful tool to analyze nonlinear/nonstationary signals (e.g., vibration signal). The intrinsic vibration mode of a gearbox can be extracted by EMD [5]. However, EMD suffers from mode-aliasing and spurious-mode problems [5]. That is, two different vibration modes may mix with each other in the outputs of EMD. The CEEMDAN improves the original EMD by adding a finite number of adaptive white noise in the decomposition process. The mode-aliasing and spurious modes can be solved by CEEMDAN [5]. The implementation of CEEMDAN can be described briefly as the following six steps.

Step 1: Compute the first residue of the signal $x(t)$ by Eq. (1).

$$r_1(t) = \left\langle M(x(t)^{(n)}) \right\rangle \tag{1}$$

where, M(·) denotes the local mean operator; $x(t)^{(n)} = x(t) + \beta_1 E_1[\sigma(t)^{(n)}]$ (n = 1, 2,…, N) denotes the ensemble of the signal x with N realizations of zero mean unit variance white noise $\sigma(t)$; $E_k(\cdot)$ (k = 1, 2,…, K) denotes the kth mode generated by EMD decomposition and β_k is a constant coefficient to $E_k(\cdot)$; <·> denotes the averaging operator. So the first CEEMDAN mode can be obtained by

$$d_1(t) = x(t) - r_1(t) \tag{2}$$

Step 2: Calculate the kth residue by Eq. (3).

$$r_2(t) = \left\langle M(r_1(t) + \beta_2 E_2(\sigma(t)^{(n)})) \right\rangle \tag{3}$$

where,. The second CEEMDAN mode is derived by

$$d_2(t) = r_1(t) - r_2(t) \tag{4}$$

Step 3: Calculate the rest residues (k = 3, 4,…, K) and modes by Eq. (5).

$$\begin{cases} r_k(t) = \left\langle M(r_{k-1}(t) + \beta_k E_k[\sigma(t)^{(n)}]) \right\rangle \\ d_k(t) = r_{k-1}(t) - r_k(t) \end{cases} \tag{5}$$

2.3. Recurrence Technology

Phase space reconstruction. The state of a system at certain points is called phase, and its geometry space is called phase space. The phase construction allows single variable time series to extend into a high dimension space. In order to obtain the comprehensive information and reproduce the dynamics characteristics of the gearbox system, it is necessary to reconstruct the phase space of the gear vibration time series. The Takens theorem [3] indicates that the phase space of a system response can be reconstructed using appropriate embedded dimension and the delay time.

Assume a time series $\{y_i\}$ (i = 1, 2,…, I and I is the number of data points). It can be reconstructed to a m-dimension phase space as $\mathbf{Y} = [Y_1, Y_j, \ldots, Y_J]^T$ and

$$Y_j = \left[y_j, y_{j+\tau}, y_{j+2\tau}, \ldots y_{j+(m-1)\tau} \right] (j = 1, 2, \ldots, J) \tag{6}$$

where τ is the delay time and m is the embedding dimension, J (= I – m + 1) is the number of the phase space vector. Obviously the premise of phase space construction is how to confirm the values of τ and m. If $\{y_i\}$ is a group of real-time series, τ can be selected by Eq. (7) [4]

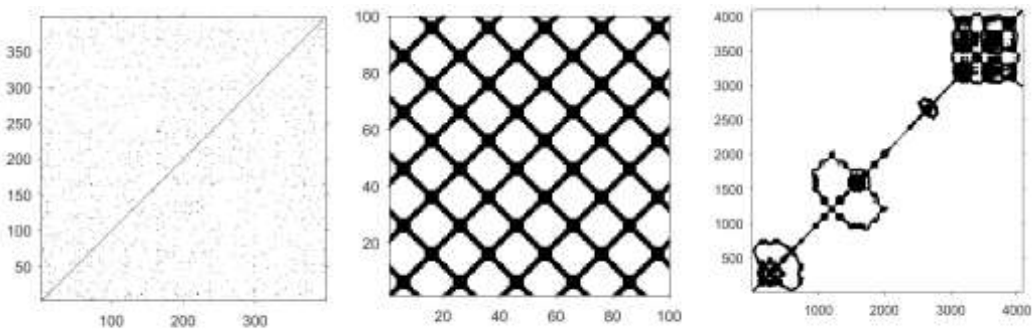
$$C(\tau) = \frac{\frac{1}{I-\tau} \sum_{i=1}^{I-\tau} \left[y(i+\tau) - \bar{y} \right] \left[y(i) - \bar{y} \right]}{\frac{1}{I-\tau} \sum_{i=1}^{I-\tau} \left[y(i) - \bar{y} \right]^2} \tag{7}$$

where $\bar{y}$ is the average of $\{y_i\}$ and $C(\tau)$ is the autocorrelation. The time delay τ is determined when $C(\tau)$ firstly drops to less than or equal to (1 - 1/e) times of its initial value. The embedded dimension m can be obtained by the false nearest neighbors method [4].

Recurrence plot and Recurrence quantitative analysis (RQA). Recurrence plot is a two-dimensional graphical representation of the dynamic system trajectory in the form of binary recurrence matrix $\mathbf{R} = \{R_{i,j}\}$ (i, j = 1, 2,…, J), which can be expressed as

$$R_{i,j} = \Theta(\varepsilon - \left\| Y_i - Y_j \right\|) \tag{8}$$

where ε is the threshold distance, $\|\cdot\|$ is the Euclidean norm operator in the phase space, and $\Theta(\cdot)$ is the Heaviside function. There are three patterns in the recurrence plot, namely, homogeneous, cycle, and mutation modes [3]. Fig. 1 depicts these three patterns. In Fig. 1(a) the homogeneous mode displays a random distribution of the recurrence points, which probably indicates a normal condition of the system. In Fig. 1(b) periodical distribution is found in the cycle mode, suggesting some abnormalities in the system. Fig. 1(c) presents significant chaos in the mutation mode, which means that severe damages occur in the system. Hence, these three modes reflect the characteristics of a dynamic system in different states.



(a) (b) (c)

Fig 1. Three patterns of recurrence plot: (a) homogeneous, (b) cycle, and (c) mutation modes.

Based on the recurrence plot, the quantitative recurrence analysis uses some chaotic parameters to quantitatively describe the distance between the recurrence points and the graph topology. These parameters include the RR, DET, ENTR and LAM [3]. The RR refers to the ratio of recurrence points to the total points in a given reference distance.

$$RR = \frac{1}{J^2} \sum_{i,j=1}^{J} R_{i,j}(\varepsilon) \tag{9}$$

The DET refers to the ratio the recurrence points in the diagonal segment paralleling to the recurrence plot diagonal.

$$DET = \sum_{l=l_{\min}}^{J} lP_l \Big/ \sum_{l=1}^{J} lP_l \tag{10}$$

where P_l is the probability of diagonal distribution with the length l, and $l_{\min}$ is the minimum diagonal length.

The LAM refers to the sum of the percentage of recurrence points contained in the vertical structure of each vertical line segment.

$$LAM = \sum_{v=v_{\min}}^{J} vP(v) / \sum_{v=1}^{J} vP(v) \tag{11}$$

where P_v is the probability of vertical distribution with length v, and $v_{\min}$ is the vertical length of the minimum points among the vertical lines.

The ENTR is the Shannon entropy of the line segments paralleling to the recurrence plot diagonal.

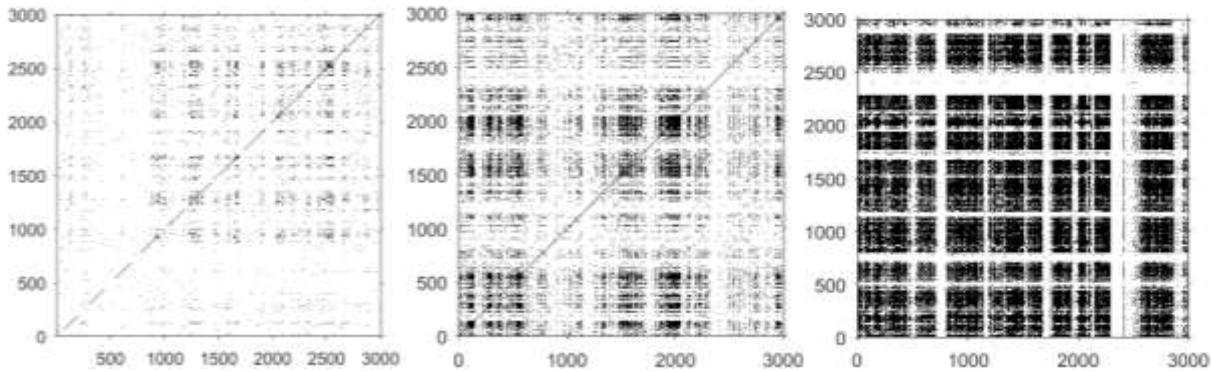
$$ENTR = -\sum_{l=l_{\min}}^{J} p_l \ln p_l \tag{12}$$

3. Experimental Results and Discussions

Fig. 2 shows the experimental tester for the coal cutter gearbox. The tester is consisted of a motor driver, an electrical load, a motor speed controller, a two-stage gear transmission system, and a data acquisition system. The transmission flow of the gears is as input→Z26→Z64→Z40→Z85→output.

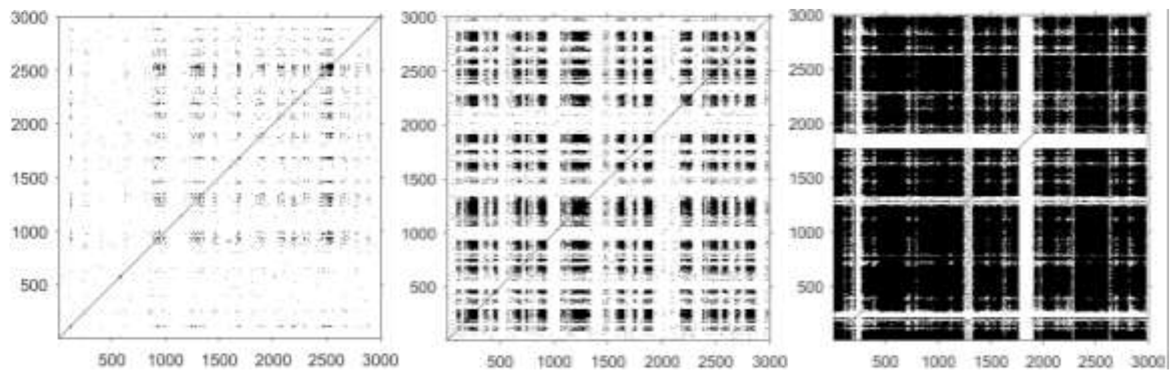
Fig. 2. The gearbox tester: (left) the testing system and (right) the gearbox configuration.

The incipient failures of the Z26 gear, i.e., wear and crack, were tested in the experiments. Two piezoelectric accelerometers (CA-YD-106) were mounted on the intermediate and output shafts of the gearbox. The sample frequency was 20 kHz, the driver speed was 750 rpm. The proposed IQRA method was applied to the vibration signals of the gearbox. Figs. 3-5 compare the analysis results using the original QRA, EMD-based QRA and the proposed IQRA. Fig. 3 provides the recurrence plots of the gear vibrations under normal, wear and crack conditions using the original QRA method. It can be seen in Fig. 3(a) that the pattern in the recurrence plot of the normal gear was very close to the homogeneous pattern although some periodical components appeared in the shape of squares. These periodical components were probably caused by (1) background noise in the raw vibration signal and (2) the slight wear of the gears in the running-in process. Fig. 3(b) presents obvious periodical components in the shape of squares in the recurrent plot of worn gear, which demonstrated that the gear wear produced the square pattern (i.e., cycle mode). Furthermore, under gear crack condition clear square pattern can be observed as the dominant components in Fig. 3(c). Thus, with the increase of fault severity, the square pattern becomes clearer. Similar observations were obtained in Figs. 4 and 5 using EMD-QRA and IQRA. However, comparing with Fig. 3 it can be noticed that the noise has been significantly reduced in the recurrent plots in Fig. 4 & 5. In addition, the square patterns in Fig. 5 were clearer than these in Fig. 4. Hence, the proposed IQRA outperformed EMD-QRA with respect to the noise degree. Based on the recurrence plots, the qualitative analysis was then used to calculate the chaotic parameters for the gearbox. It is able to achieve quantitative assessment for accurate gear fault diagnostics rather than observing the recurrence plots. Fig. 6 depicts the ENTR curves for the vibration signals under different operation conditions using the three methods. Each computation cycle used 1/10 data points in the time series to calculate the ENTR.



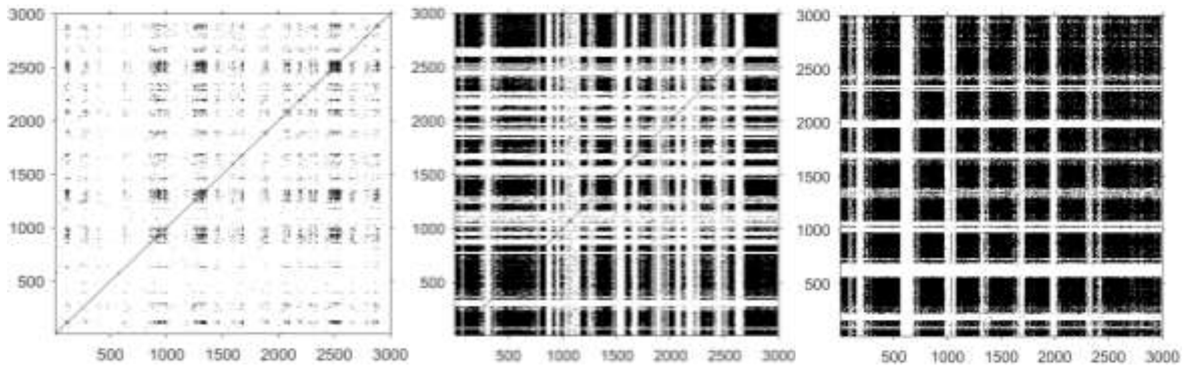
(a) (b) (c)

Fig. 3. The recurrence plots produced by QRA: (a) normal, (b) worn and (c) cracked gears.



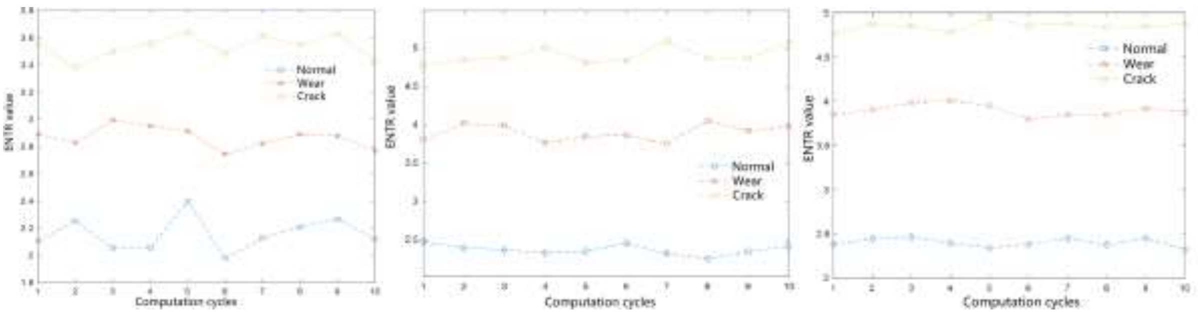
(a) (b) (c)

Fig. 4. Recurrence plots produced by EMD-QRA: (a) normal, (b) worn and (c) cracked gears.



(a) (b) (c)

Fig. 5. Recurrence plots produced by IQRA: (a) normal, (b) worn and (c) cracked gears.



(a) (b) (c)

Fig. 6. The recurrence quantitative analysis using (a) QRA, (b) EMD-QRA and (c) IQRA.

As can be seen in Fig. 6(a), the ENTR curves produced by the original QRA were not smooth due to noisy points. Because the ENTR difference between the normal, worn and crack gears was less than 0.8, the noisy points may result in misdiagnosis. On the contra, smooth ENTR curves were obtained by the EMD-QRA and IQRA methods with an inter-condition distance of almost 1.0 in Figs. 6(b) and (c). The gear fault quantitation performance of EMD-QRA and IQRA is better than that of QRA. The reason is that the background noise and disturbance were eliminated/reduced greatly by the EMD and CEEMDAN. Furthermore, the average monotonicity of the three ENTR curves generated by each method was calculated. The results were 0.53, 0.78 and 0.84 for QRA, EMD-QRA and IQRA, respectively. A larger average monotonicity means better fault quantitation performance. As a result, the proposed IQRA is superior to the other two methods in terms of fault quantitation. Similar observations were also found in the other three chaotic parameters, i.e., RR, DET, and LAM. The analysis results demonstrated that the proposed IQRA is effective and reliable for quantitative identification of the gear incipient failures.

4. Conclusions

It is widely recognized that the coal energy is of significant and indispensable resource in the economic development of China. Due to hostile working condition, the transmission parts of the coal cutters frequently damage. So monitoring the transmission parts of coal cutters has become the main focus and received considerable attentions from both academia and industry. Considering that the gear transmission system can be characterized by chaos and fractal characteristics, this paper proposes a new diagnosis method based on the chaos theory, i.e., the improved quantitative recurrence analysis (IQRA) method. The proposed IQRA is expected to enable to extract the intrinsic vibration mode of the gearbox and quantify the gear faults. To our best knowledge, it is the first time in the literature that the CEEMDAN is appropriately incorporated into the quantitative recurrence analysis for gear incipient fault detection. Experimental evaluation demonstrated that the recurrence plots of the proposed IQRA characterized significant differences between different gear operation conditions. An increasing trend of chaotic motion was discovered with the increase of gear fault severity. In addition, the curves of the extracted quantitative fault indicators correctly distinguished different gear operation conditions. Compared these results with those obtained from original QRA and EMD-QRA, thanks to CEEMDAN denoising process, the proposed IQRA provided smoother quantitative-indicator curves and better gear fault detection performance than that of its competitors. Since the gear incipient faults were used to in the experimental evaluation, the proposed method has addressed one of the most important and challenging tasks in the gear fault diagnosis. The effectiveness of the proposed IQRA method in gear incipient fault detection manifests great potentials for practical applications. Further work will develop a diagnosis system based on the proposed method for real-world practice.

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