# The Fault extent recognition method of rolling bearing based on orthogonal matching pursuit and Lempel-Ziv complexity

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**Abstract:** The fault extent recognition technology of rolling bearing is crucial to the condition-based maintenance. A Lempel-Ziv complexity based assessment method is proposed combined with orthogonal matching pursuit algorithm. The measured original vibration signal is processed by orthogonal matching pursuit algorithm to reduce the effect of noise, and then the Lempel-Ziv complexity is calculated as an index of bearing performance. A fault extent recognition experiment is conducted, and the results indicate that the presented method could effectively and accurately conduct the fault extent recognition of rolling bearing.

**Keywords:** Rolling bearing; performance degradation assessment; orthogonal matching pursuit; Lempel-Ziv complexity

## 1 Introduction

The rolling bearing is a critical part in the rotating machinery, its failure may cause high-cost downtime, or even disastrous failure of the whole machinery due to the severe working condition. However, the regular maintenance schedule often brings insufficient or excess maintenance problem, and still couldn't prevent the sudden failure of rolling bearing. Recognizing the necessity of the condition assessment and degradation trend of rolling bearing, the condition-based maintenance aiming to cut down the maintenance cost attracts more and more attention [1]. Therefore, the fault extent recognition technology of rolling bearing has become a research focus in the Prognostic and Health Management (PHM) field of rolling bearing [2, 3].

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The feature extraction technology of vibration signal is the investigation basis of performance degradation of rolling bearing, the traditional time domain [4, 5] or frequency domain parameters [6, 7], such as root-mean-square, kurtosis, the amplitude of characteristic frequency, can't accurately represent the rolling bearing condition. Combined with the theory of entropy, Huang and Zhao et al. [8, 9] presented EMD energy entropy and EMD approximate entropy to analyze the performance degradation trend of rolling bearing. Due to the increasing complexity of modern machinery, the time-frequency domain parameters can't satisfy the requirement of performance degradation of rolling bearing either. As a time-frequency analysis method, the matching pursuit (MP) has a flexible and adaptive basis function and has been successfully used in bearing fault diagnosis due to the high signal-to-noise ratio of extracted vibration feature [10]. Cui et al. [11] presented an adaptive matching pursuit to realize the fault diagnosis of bearing and exhibited an excellent efficiency and stability.

Yu [12] developed an adaptive-learning-based method for health degradation monitoring, and further proposed an adaptive hidden Markov model-based health index that quantifies the similarity between the historic and current health condition of bearing. Jensen Rényi divergence (JRD) is able to quantify the deviation between probability distribution of bearing condition, Singh et al. [13] presented a JRD parameter to analyze the degradation trend of bearing condition. Based on fuzzy c-means[14] and k-medoids clustering [15], The confidence value between test and normal data is obtained as an assessment index of bearing degradation, but the model training must be conducted first utilizing normal and failure vibration data. Fractal dimension is an approach to describe the complexity degree of fractal set, Wang et al. [16] proposed a performance degradation character based on mathematical morphological fractal dimension which has a favorable relevance with performance degradation degree of rolling bearing. In the recent years, the Lempel-Ziv complexity (LZC) was investigated for evaluating the bearing fault extent. Combined with EMD and local mean decomposition algorithm, Dou et al. [17, 18] developed severity recognition models of bearing fault.

The remainder of this paper is organized as follows. In the first and second section respectively illuminate the basic principle of orthogonal matching pursuit and Lempel-Ziv complexity, and the proposed assessment method based on the above two algorithm. The third section applies two rolling bearing experiments with outer race fault to validate the effectiveness of proposed assessment method.

## 2 Basic principles of related algorithm

### 2.1 Orthogonal matching pursuit

The orthogonal matching pursuit is an iterative greedy algorithm for signal approximation. The basic principle of OMP is to assure that the obtained residual signal is orthogonal to all matching atom in every iteration [19]. The detailed iteration steps are as follows.

(1) Determine an over-complete atom dictionary $D = \left\{ g_\gamma ,\ \left\| g_\gamma \right\| = 1 \right\}_{\gamma \in \Gamma}$ , $\Gamma$ is the index set of atom dictionary. Initialize the original signal *y*, and the initial residual signal $R^1 = y$ ; the chosen matching atom set $\psi_0 \in \varnothing$ , the residual ratio $\sigma$ and the number of iteration

$k = 1$.

(2) Find the index $\gamma$ such that $\left|\left\langle R^k, g_\gamma^k \right\rangle\right| = \sup_{\gamma \in \Gamma} \left|\left\langle R^k, g_\gamma \right\rangle\right|$.

(3) Update the index set $\Gamma = \Gamma \bigcup \{\gamma\}$, and the chosen matching atom set $\psi_k = \psi_{k-1} \bigcup \{g_\gamma^k\}$.

(4) Update the residual signal $R^{k+1} = R^k - \left|\left\langle R^k, g_\gamma^k \right\rangle\right| g_\gamma^k$. Therefore, after $n$ iteration the original signal $y$ could be decomposed as

$$y = \sum_{k=1}^{n} \left\langle R^k, g_\gamma^k \right\rangle g_\gamma^k + R^{n+1}$$

(5) Ask if $\left\|R^k\right\|_2 \big/ \left\|y\right\|_2 < \sigma$, if not, let $k = k+1$, return to step 2 and continue to iterate; if so, terminate the iteration, output the reconstructed signal $x = \sum_{k=1}^{n} \left\langle R^k g_\gamma^k \right\rangle g_\gamma^k$ and the approximate error $R = y - x$.

## 2.2 Lempel-Ziv complexity

Lempel-Ziv Complexity (LZC) was first proposed by Abraham Lempel and Jacob Ziv [20] to measure the complexity extent of finite time sequence. The coarse graining processing of original signal is a critical step for calculating the LZC, and the binarization processing is the most popular processing approach recently. The detailed LZC calculation process is listed as follows.

(1) The binarization processing of original numerical sequence. For the original numerical sequence $x(n)$, if $x(i) \geq mean(x(n))$, $(i = 1, 2, \cdots, n)$, let $S(i)=1$; otherwise, let $S(i)=0$. After binarization processing, the symbol sequence is obtained as $S(N) = \{S_1, S_2, \cdots, S_N\}$.

(2) Initialize the relevant algorithm parameters. Setting $r=0$, initialize the temporary character variable $S_{v,0} = \{\ \}$ and $Q_0 = \{\ \}$, complexity $C_N(0)=0$. When $r=1$, let $Q_1 = \{Q_0 s_1\}$; $Q_1$ does not belong to $S_{v,0}$, therefore, $C_N(1)=C_N(0)+1=1$, $Q_1 = \{\ \}$, $r=r+1$.

(3) Calculate the complexity. Let $Q_r = \{Q_{r-1} s_r\}$, $S_{v,r-1} = \{S_{v,r-2} s_{v,r-1}\}$, ask if $Q_r$ belongs to $S_{v,r-1}$. If so, $C_N(r)=C_N(r-1)$ and $r=r+1$; if not, $C_N(r)=C_N(r-1)+1$, $Q_r = \{\ \}$ and $r=r+1$. Repeat step (3), and loop $n$ times. According to reference [21], empirical values of $n$ should satisfy $n \geq 3600$.

(4) According Eq. (1), the normalized complexity is finally obtained as

$$C = \frac{C_N(n)\log_l N}{N} \tag{1}$$

Where, when binarization processing is conducted, $l = 2$.

## 3 Assessment method based on OMP and LZC

The process diagram of LZC-based degradation assessment method combined with OMP is shown in Fig. 1. First, the vibration signal of rolling bearing in a certain condition is measured, and the obtained original signal $y$ is introduced in OMP algorithm for noise reduction. Then, the reconstructed signal *x* is obtained through the chosen matching atom set, and the symbol sequence S(N) is obtained through the binarization processing of *x*. Calculating the complexity of sequence S(N), and finally the LZC index which assesses the bearing condition is obtained after the normalization of complexity according to Eq. (1).

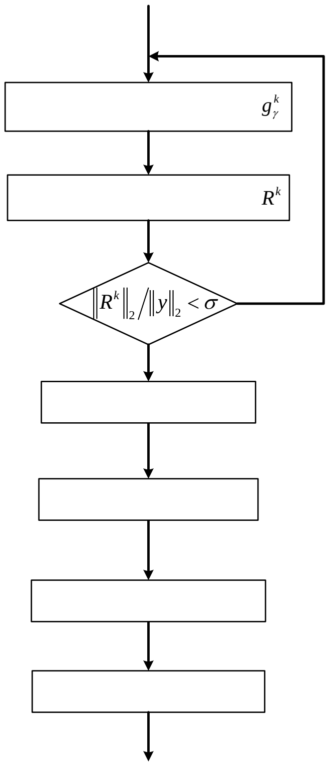


**Fig. 1.** The process diagram of proposed assessment method.

## 4 Experiments validation and results analysis

Firstly, the experimental data from Case Western Reserve University is used for fault extent recognition of rolling bearing [22], and the test rig is shown as Fig. 2. The single-point faults, including outer raceway, inner raceway and rolling element fault, are introduced into 6205-2RS JEM SKF bearing at drive end, and this study only applies the vibration data of outer raceway fault with fault diameters of 7, 14 and 21 mils (1 mil = 0.001 inches). To verify the feasibility of proposed index in different operating conditions, the motor load is selected as 0, 1, 2 and 3 HP (horsepower) separately.

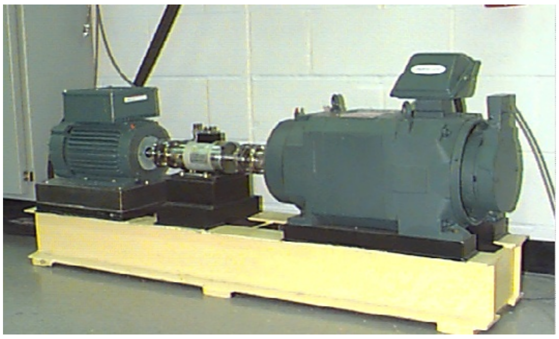

**Fig. 2.** The test rig in Case Western Reserve University

Take the vibration data of rolling bearing with outer raceway fault diameters of 7 mils as a case, the data file contains 121991 sample points. In order to increase computation efficiency, the data segment contained 10240 points was cut from measured original vibration signal. According to the orthogonal matching pursuit algorithm, the original vibration signal is processed. The waveform and spectrum of original vibration signal and reconstructed signal are shown in Fig. 3 and Fig. 4, separately.

**Fig. 3.** Measured original signal (7 mils and 0 HP)


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**Fig. 4.** Reconstructed signal (7 mils and 0 HP)

Then, the binarization processing of reconstructed signal is conducted, and the LZC index of obtained symbol sequence is computed based on Lempel-Ziv complexity. After finishing the computation of all the vibration signals, the results of LZC indexes are all listed in Table 1. The results indicate that the LZC indexes are restricted in a certain interval for a definite fault diameter, although the motor load varies. The Fig. 5 shows that in the same motor load condition, the LZC indexes also present an increasing trend with the fault diameter increasing. Besides, the motor load doesn't have an obvious effect on the LZC index.

**Table 1.** The LZC indexes of different fault diameters

| Fault diameter / mil | Motor load / HP | LZC index |
|---|---|---|
| 7 | 0 | 0.3987 |
| | 1 | 0.3778 |
| | 2 | 0.3972 |
| | 3 | 0.4415 |
| 14 | 0 | 0.4291 |
| | 1 | 0.4710 |
| | 2 | 0.4753 |
| | 3 | 0.5445 |
| 21 | 0 | 0.6586 |
| | 1 | 0.6293 |
| | 2 | 0.6277 |
| | 3 | 0.6267 |

The Fig. 5 shows that in the different motor load conditions, the LZC indexes always keep a increasing trend while the fault diameter increasing. Through the LZC index computation of different fault diameters of outer raceway, the results manifest that the proposed LZC index can comparatively effectively recognize the different fault extents of rolling bearing in different working conditions based on the orthogonal matching pursuit algorithm and Lempel-Ziv complexity.

**Fig. 5.** The trends of LZC indexes in different motor load conditions

## 5 Conclusion

For the fault extent recognition of rolling bearing, a Lempel-Ziv complexity-based assessment method combined with orthogonal matching pursuit algorithm is proposed. The rolling bearing experiments with outer race fault are used to validate the performance of the presented assessment method. Through the recognition test of different outer race fault extents, it is able to accurately recognize different fault extents in different load conditions.

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