

Order component extraction technology for predictive maintenance system in rotary machine

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Abstract. The most obvious difference between the recent smart factory and the traditional automation factory is that the techniques about Predictive Maintenance (PdM) are introduced, PdM is also one of the key enabling technologies in Industry 4.0. In general, the smart factory that employs PdM intelligently ensures efficient and reliable industrial operations. The intelligent maintenance and fault diagnosis of rotating machinery, a core component of smart factories, is crucial. Due to the large speed fluctuation of manufacturing equipment in smart factory, its condition signal often presents multi-component property combination with fast-varying instantaneous frequency. However not much has been done in terms of PdM for smart factory and very few works tries to deal with time-varying multiple components extraction. Different failures for smart factory are attributable to the lack of research on PdM under large speed fluctuation. This work details a an order component extraction model according to Synchronous Extraction Transform (SET) combination with Vold-Kalman Filtering (VKF), The model extracts instantaneous frequency based on the time-frequency distribution, effectively avoiding the problem of spectral blurring. Additionally, by combining VKF technology, it accurately extracts the order components of condition signal. Finally, this paper develops an order component extraction system, it mainly consists of a signal acquisition module, and data processing module with good application prospect and promotion value in smart factory.

Keywords: Rotary machine / predictive maintenance / large speed fluctuations / order component extraction / system development

1 Introduction

In the vision of fourth industrial revolution, smart factories are fully automated production plants where industrial information system automatically monitors the equipment's operation throughout the entire process [1]. Smart factories necessarily must adopt fully PdM to achieve above goal. Fault diagnosis of rotating machinery holds significant importance in intelligent factories, as these machines are integral components within such environments. The uninterrupted and efficient operation of rotating machinery is crucial for the overall stability and productivity of production lines. Any malfunction in these critical pieces of equipment can lead to production halts and potentially cause a complete breakdown of

the production line. Therefore, implementing intelligent maintenance and fault diagnosis for rotating machinery is essential. These measures not only facilitate the early detection and prevention of potential issues but also ensure the continuous and efficient functioning of production systems. Consequently, this enhances the overall operational capabilities and reliability of intelligent factories. Employing advanced fault diagnosis techniques is of paramount importance for achieving efficient production management and informed maintenance decision-making.

Considering the equipment in smart factory often works under variable operating condition, its condition signal obtained by industrial information system presents fast-varying instantaneous frequency and multi-component drastically. Besides, non-stationary working condition also leads the condition signal to produce complex amplitude modulation and frequency modulation phenomenon, which brings difficulties to diagnose fault by using traditional

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diagnostic methods [2]. As the order component is a key monitoring indicator in industrial information system, its accurate extraction is not only an important characteristic parameter reflecting the smart factory's operating state, but also significant for PdM under unsteady operating condition consequently [3,4]. Intelligent factories face non-stationary environmental factors such as variable speeds, load changes, and equipment failures, which complicate the operational status of equipment. Traditional periodic inspections struggle to timely detect potential faults, leading to downtime and reduced production efficiency. Predictive Maintenance (PdM), however, monitors equipment status in real-time and uses data analysis techniques to predict faults in advance. PdM dynamically adapts to equipment changes, accurately identifies health statuses, and predicts fault types and timings, thereby reducing downtime, improving equipment reliability, and maximizing production efficiency.

Traditionally precise measurement methods of instantaneous rotational frequency often employ speedometer combined with displacement sensors. In recent years, optical encoders have been widely used and above technologies can generally meet current accuracy requirement. However, in many application fields, it is difficult to install these devices, thus failing to obtain accurate instantaneous rotating frequency, which poses challenges for assessing and diagnosing the healthy condition, as a result, it is necessary to precisely estimate instantaneous rotating frequency by solely processing and analyzing vibration signal in the absence of testing device. Gao [5] combined narrowband phase demodulation and Hilbert transform technology to estimate the instantaneous rotating speed of gearbox equipment. Gryllias et al. [6] and Gomez et al. [7] employed short-time scale transformation method to process vibration signal and further extracted fluctuating information of instantaneous rotational frequency. However, these aforementioned methods are limited to the case of finite rotational speed fluctuation. Addressing these shortcomings, Kowalski et al. [8] and Yi et al. [9] proposed an instantaneous rotating frequency estimation method based on harmonic signal decomposition, transforming the estimation method into an eigenvalue extraction issue. Yet, this method exhibits high sensitivity to background noise.

Time-frequency analysis methods offer a new approach for estimating instantaneous rotating frequency, such that Short-time Fourier transform (STFT) combination with ridge line searching strategy has been widely applied on mechanical equipment monitoring and diagnostics [10–12]. However, the effectiveness of STFT depends on the assumption of local stationary, which is not suitable for rapidly varying instantaneous rotating speed condition. Considering time-frequency reassignment methods involve in reprocessing time-frequency transformation, rearranging the distribution of time-frequency energy to enhance time-frequency localization [13], it can be utilized to instantaneous rotating frequency estimation. On the other hand, traditional time-frequency reassignment methods lack reversibility and therefore cannot reconstruct signal in the time-domain. In contrast, synchronous transform methods rearrange signal's time-frequency representation

solely in the frequency direction, providing a reconstructive property [14, 15]. However, it neglects the signal's time-frequency energy distribution in the time direction, thereby limiting its applicability on vibration signal possessing a slowly varying instantaneous rotating frequency [16–18]. The Synchrosqueezed Transform (SET) is an advanced time-frequency analysis method designed to improve the resolution and accuracy of time-frequency representations. Compared to the traditional Short-Time Fourier Transform (STFT), SET achieves a clearer time-frequency representation by redistributing energy on the time-frequency plane. SET enhances the resolution of time-frequency representations by reallocating energy to more precise locations on the time-frequency plane. This allows SET to better separate different frequency components when dealing with complex signals [19–21]. In the fault diagnosis of rotating machinery systems, accurately extracting order components is crucial for identifying and analyzing fault characteristics. The Vold-Kalman Filter (VKF), as an advanced signal processing tool, has gained widespread attention for its superior performance in processing non-stationary signals. VKF achieves precise estimation of order components in the time domain by constructing a state-space model. VKF can decompose complex multi-component signals into a sum of multiple single-component signals and residual signals. Its center frequency can be adaptively adjusted according to the instantaneous frequency, effectively separating signal components that are adjacent or even intersecting in the time-frequency domain [22–24]. Compared to traditional filtering methods, VKF can directly extract the signal components of interest from the time domain, avoiding phase bias caused by time-frequency domain transformations. In recent years, VKF has been widely applied in various engineering fields.

This paper adopts a method combining Vold-Kalman Filtering (VKF) and Synchrosqueezed Transform (SET) to achieve keyless instantaneous speed estimation and order component extraction. Firstly, a simulation signal including linear speed variation, speed fluctuation, and large fluctuation rapid speed varying stage is set up, through SET and peak search strategy, we can estimate high-precision instantaneous rotating frequency, which are used as instantaneous frequency parameters for VKF. This allows us to directly achieve the separation of complex multi-component non-stationary signal in the time domain and transform them into a combination of multiple single-components and residual component. Secondly, through semi-physical simulation in the laboratory, we generated two linear frequency sweep signals using a signal generator. By applying the proposed method in this paper, we successfully extracted the instantaneous frequencies and corresponding order components in vibration signal. Finally, by using rolling bearing fault vibration experiment, it also validates the effectiveness and reliability of the proposed method in this paper.

To achieve instantaneous speed estimation and order component extraction under large speed fluctuation, a system for order component extraction based on combined programming with LabVIEW and MATLAB was developed. This system aims to provide efficient and accurate solution to meet the stringent requirement of engineering

application. The system mainly consists of a signal generation module, a signal acquisition module, and a data processing module. The signal generation module is responsible for generating simulated vibration signal, and the signal acquisition module transmits the vibration signal collected by sensors to the computer through a high-speed data acquisition card. The data processing module uses MATLAB to process and analyze the collected signal, achieving instantaneous frequency estimation and order component extraction. Through this system, we can achieve high-precision signal analysis under complex working condition, significantly improving the reliability and efficiency of engineering application.

2 Theoretical foundation

2.1 Keyless instantaneous rotational speed estimation based on synchrosqueezed transform (SET)

In the presence of substantial velocity fluctuation, the vibration signal displays notable alteration on frequency, amplitude modulation, non-stationarity, and the presence of noise interference. Vibration signal subjected to significant speed fluctuation displays pronounced non-stationary characteristics. As a consequence of the speed fluctuation rapidity, the vibration signal's frequency also undergoes a varying trend, resulting in the movement and overlap of spectrogram. The application of traditional steady-state spectral analysis methods (such as FFT) are hindered by inherent limitations, rendering the extraction of effective fault features faces a challenging endeavour. The existing speed estimation methods face two significant drawbacks: a slow response time and a high sensitivity to noise under large speed fluctuation condition. Some speed estimation methods exhibit a delayed response to rapidly changing speed, rendering them unable to track varying speed in a timely manner. Furthermore, the existing speed estimation methods are more sensitive to noise, and the impact of noise becomes more pronounced under large speed fluctuation condition, leading to a concomitant decrease in estimation accuracy.

The Synchrosqueezed Transform (SET) is a novel time-frequency analysis method for non-stationary signal. It is a time-frequency reassignment method that can improve the concentration of time-frequency representations. SET redistributes the time-frequency representation of the Short-Time Fourier Transform (STFT), so its theoretical derivation often starts from STFT. STFT can be defined as following.

$$G(t, \omega) = \int_{-\infty}^{\infty} g(u-t) \cdot s(u) \cdot e^{-j\omega u} du \quad (1)$$

where $g(u-t)$ is the Gaussian window function, the phase shift factor $e^{j\omega t}$ is added to the STFT result $G(t, \omega)$, according to Parseval's theorem, the STFT expression can be modified as $G_e(t, \omega) = \int_{-\infty}^{\infty} g(u-t) \cdot s(u) \cdot e^{-j\omega(u-t)} du$.

The essence of SET is to add the synchrosqueezing Operator (SEO) into the STFT result to extract the time-frequency coefficients at the time-frequency ridges of $G_e(t, \omega)$. The time-frequency expression of SET is as follows.

$$T_e(t, \omega) = G_e(t, \omega) \cdot \delta(\omega - \omega_0(t, \omega)) \quad (2)$$

Where $\delta(\omega - \omega_0(t, \omega))$ represents the SEO, and $\omega_0(t, \omega)$ is the instantaneous frequency. For any range of (t, ω) , when $G_e(t, \omega) \neq 0$, the following operation is performed on $G_e(t, \omega)$ $\omega_0(t, \omega) = \frac{G_e(t, \omega)}{j \cdot G_e(t, \omega)}$. By using the δ function (unit impulse function), only the time-frequency coefficients with the maximum energy on the time-frequency ridge ($\omega = \omega_0$) are retained, resulting in a well-focused time-frequency analysis effect.

In the SET method, the window function length plays a critical role in the resolution of time-frequency analysis. A shorter window function can improve time resolution, accurately capturing the signal's instantaneous changes, but it will reduce frequency resolution, leading to blurred frequency information. Conversely, a longer window function enhances frequency resolution, clearly separating frequency components, but decreases time resolution, making it difficult to capture instantaneous changes. To balance time and frequency resolution, this study sets the window function length based on a proportion of the signal length, defaulting to one-eighth of the signal length. This setting allows us, under variable rotational speed conditions, to obtain fine frequency information while maintaining sensitivity to instantaneous changes. Additionally, this parameter can be adjusted according to specific signal characteristics to meet different application requirements.

In the scenarios of significant speed fluctuation, mechanical fault vibration signal displays a rapid alternation in both their instantaneous frequency and modulation property. SET can concentrate the signal's energy at the instantaneous frequency, effectively increasing the energy concentration of time-frequency representation. This allows for more accurate extraction of instantaneous frequency and maintains high frequency and time resolution even in noisy environment, effectively suppressing noise interference. This paper accurately extracts instantaneous frequency by applying the synchrosqueezed transform to vibration signal, achieving precise speed estimation under large speed fluctuation.

2.2 Ridge line detection

The ridge detection algorithm can more accurately estimate the signal's instantaneous frequency (IF), which is beneficial for extracting order components using VKF. Scholars have conducted extensive research on ridge detection methods based on time-frequency distribution. Reference [25] detects the signal's IF by finding the maximum value in the time-frequency representation. This method is simple to implement but highly susceptible to noise or other component interference.

Reference [26] simultaneously extracts all signal components by calculating the local maxima of a specific function, but the number of components must be determined in advance. In actual vibration signal, it is extremely difficult to determine the number of components due to interference from different components and noise. Moreover, this method estimates all components simultaneously, which can lead to algorithm instability and errors in the extracted IF, making it difficult to apply in practice.

This paper will use the ridge detection method from [27], it can estimate the IF information of the order components with the highest energy in the vibration signal.

Considering that order component corresponding to first rotating frequency in the vibration signal generally have the highest energy, this method can be well used for instantaneous speed frequency estimation. The specific steps of the algorithm are as follows.

- Detecting the location of maximum energy in the time-frequency distribution (t_0, f_0) .
- Assuming $t_r = t_0 + 1/fs$, $t_l = t_0 - 1/fs$, $f_l = f_0$, $f_r = f_0$, where fs is the sampling frequency.
- Calculating the IF at t_l and t_r , $IF(t_l) = \tilde{f}_1$, $IF(t_r) = \tilde{f}_0$, where $\tilde{f}_1$ and $\tilde{f}_0$ are the frequencies corresponding to maximum energy at $(t_l, f_l - \Delta f) \sim (t_l, f_l + \Delta f)$ and $(t_r, f_r - \Delta f) \sim (t_r, f_r + \Delta f)$, respectively, and Δf is the maximum allowable frequency transformation.
- Assuming the values are all zero at $(t_l, f_l - \Delta f) \sim (t_l, f_l + \Delta f)$ and $(t_r, f_r - \Delta f) \sim (t_r, f_r + \Delta f)$.
- Assuming $t_r = t_r + 1/fs$, $t_l = t_l - 1/fs$.

Repeating above step 3~step5 until a series of order component are found.

2.3 Order component extraction based on Vold-Kalman filtering

The extraction of order components plays an integral role in the diagnosis of faults and the monitoring of performance in rotating machinery. The analysis of order components in rotating machinery allows for the effective identification and localisation of mechanical faults, thereby enhancing the reliability and operational efficiency of the equipment. Nevertheless, in real-world scenarios, substantial fluctuations in rotational speed present considerable obstacles to the extraction of order components. The inherent instability of rotational speed gives rise to non-stationarity in the signals, which presents a significant challenge to the efficacy of traditional order component extraction methods in accurately extracting useful feature information. The order tracking methods rely on the use of dedicated hardware devices, such as encoders or key phase sensors, while these devices offer enhanced precision, they also tend to increase the overall testing costs and present additional challenges in terms of on-site installation and maintenance. Furthermore, existing methodologies frequently prove inadequate for the effective extraction of fault features when confronted with non-stationary signal under variable speed condition, resulting in a reduction in diagnostic accuracy. The Kalman filter is a recursive algorithm that is employed to estimate a system state by reducing noise and uncertainty. By recursively updating the estimation, the system state can be updated in real time, allowing for the rapid changes in signal components under large speed fluctuation to be accommodated. This ensures the accuracy of order component extraction and enables effective handling of random noise in the system and measurement, thereby improving estimation accuracy. VKF is capable of directly extracting signal components within the time domain. This paper employs IF estimation as the reference

instantaneous frequency parameter for each component, selecting a second-order VKF filter to simultaneously extract multiple components. As the mechanical vibration fault signal often presents modulated property as shown in formula (3).

$$x(t) = \sum_{k=1}^{\infty} A_k(t) \Theta_k(t) \quad (3)$$

$$\Theta_k(t) = \exp \left[jk \int_0^t \omega(\tau) d\tau \right] \quad (4)$$

where $A_k(t)$ is the amplitude envelope of the k -th component, $\Theta_k(t)$ is the carrier signal; $\int_0^t \omega(\tau) d\tau$ is the instantaneous phase, $\omega(\tau)$ is the instantaneous frequency. The amplitude envelope can be represented as a low-order polynomial form. For discrete signals, its amplitude envelope can be expressed as in formula (5).

$$\nabla^s A_k(n) = \varepsilon_k(n) \quad (5)$$

where s is the order difference operator ($s=2$), $\varepsilon_k(n)$ is the inhomogeneous term. As a result, we can obtain formula (6).

$$A_k(n-1) - 2A_k(n) + A_k(n+1) = \varepsilon_k. \quad (6)$$

Furthermore, we can obtain the matrix form of formula (6) as shown in formula (7).

$$\begin{bmatrix} -2 & 1 & 0 & \cdots & 0 \\ 1 & -2 & 1 & \cdots & 0 \\ 0 & 1 & -2 & \cdots & \vdots \\ \vdots & \vdots & \vdots & \ddots & 1 \\ 0 & 0 & \cdots & 1 & -2 \end{bmatrix} \begin{bmatrix} A_k(1) \\ A_k(2) \\ A_k(3) \\ \vdots \\ A_k(N) \end{bmatrix} = \begin{bmatrix} \varepsilon_k(1) \\ \varepsilon_k(2) \\ \varepsilon_k(3) \\ \vdots \\ \varepsilon_k(N) \end{bmatrix}. \quad (7)$$

That is, $MA = \varepsilon$, where M is an $N \times N$ matrix.

For a measured signal $x(n)$ with noise or error term $\delta(n)$, $x(n) = \sum_k A_k(n) \Theta_k(n) + \delta(n)$, its matrix form can be expressed as in formula (8).

$$X = AB + \delta. \quad (8)$$

By extracting the time-frequency ridges using the instantaneous frequency estimation method, the instantaneous frequency $\omega_k(n)$ of the signal component can be estimated, thereby obtaining their carrier matrix B and its reconstruction form of component signal is shown in formula (9).

$$S = AB. \quad (9)$$

The significant engineering value of Kalman filter is extracting order components under large speed fluctuation. It is capable to handle complex noise environments and update data in real time, thereby ensuring the accuracy and reliability of the order components. This paper therefore applies the Kalman filter to extract order components under large speed fluctuation.

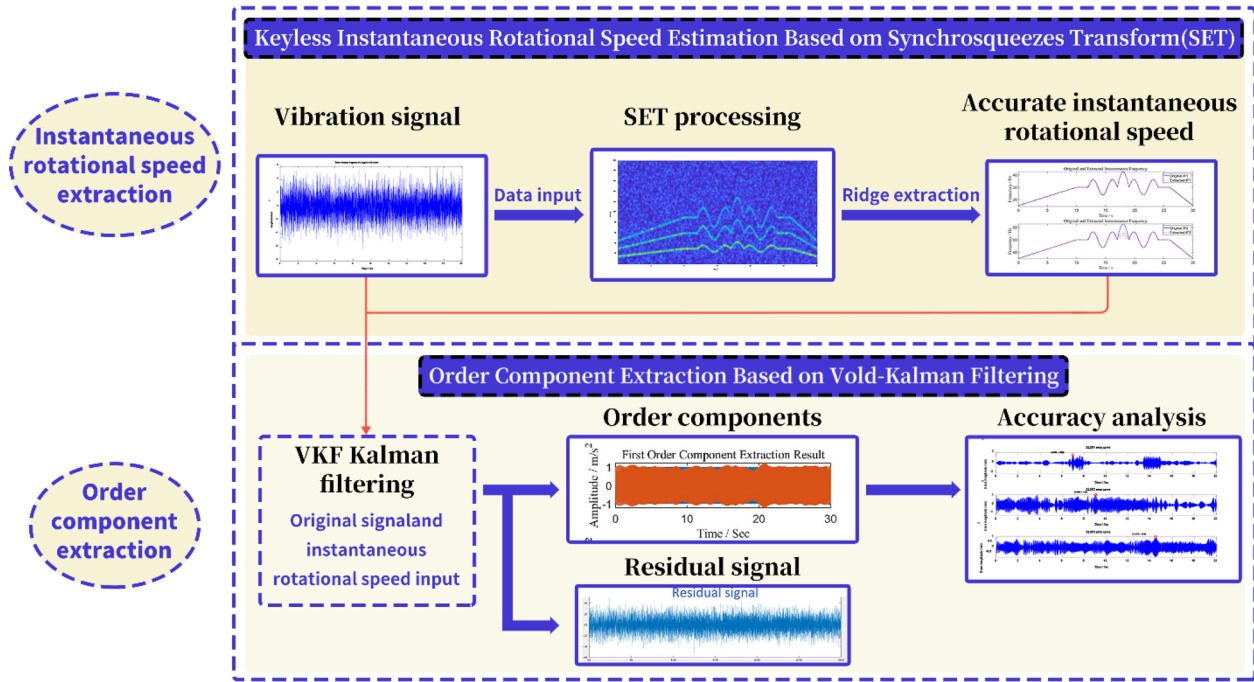


Fig. 1. Flowchart of order component extraction based on keyless phase instantaneous frequency estimation.

3 The proposed method

This paper proposes a method for order component extraction based on Synchrosqueezed Transform (SET) and Vold-Kalman Filtering (VKF). Firstly, SET is used to achieve keyless instantaneous rotational speed estimation. It can accurately estimate the instantaneous changes in rotational speed without key phase signal. This is particularly important for handling large speed fluctuation, as it can provide high-precision instantaneous speed information. Next, we use the keyless instantaneous speed to replace the measured instantaneous speed and combine it with the Kalman filter to extract order components. By using the keyless instantaneous speed as input, the Kalman filter can more effectively extract the order components from the signal, thereby improving the accuracy and reliability of signal processing.

Step one: Considering that the first-order rotational frequency order component generally possesses the highest energy in the time-frequency spectrogram, we first use the proposed keyless instantaneous rotational speed estimation method based on SET combined with ridge searching to achieve high-precision estimation of rapidly varying instantaneous speed.

Step two: Using the estimated instantaneous speed as the input parameter for the Kalman filter to extract the corresponding order component.

Step three: Subtract the extracted order component from the original signal to obtain the residual signal, and use the residual signal as the original signal for subsequent processing.

Step four: Repeat the above steps 1~3 to obtain each order components and their instantaneous frequencies. The flowchart is shown in Figure 1.

4 Simulation analysis

4.1 A rapidly varying simulation signal under speed fluctuation condition

High-end equipment is designed to operate in extreme service environments, including high speed, high temperature, rapid acceleration and strong disturbances. Aircraft engines, for instance, display pronounced time-varying, non-stationary characteristics in their fault vibration signals. This is due to the engines' frequent changes in operating conditions, significant acceleration and deceleration, and high-speed variable stiffness operation. To prove the superiority of the method proposed in this paper under extreme variable speed conditions with large speed fluctuations, a simulation signal was constructed. This simulation process accurately represents the entire mechanical equipment operation, from acceleration, constant speed, speed fluctuation, rapid speed change, to deceleration. The instantaneous angular frequency $\omega(t)$ is calculated using equation (10), and the instantaneous rotational frequency $\phi(t) = \omega(t)/2\pi$. This results in a rotational frequency curve that continuously changes over the 30-second duration.

$$w(t) = \begin{cases} 3\pi t + 30\pi & 0 < t < 10 \\ 60\pi & 10 < t < 12 \\ 60\pi + 40\sin(0.6\pi t) & 12 < t < 17 \\ 60\pi + 80\sin(0.5\pi t) & 17 < t < 19 \\ 60\pi + 40\sin(0.6\pi t) & 19 < t < 24 \\ 60\pi & 24 < t < 26 \\ 60\pi - 7.5\pi t & 26 < t < 30 \end{cases} \quad (10)$$

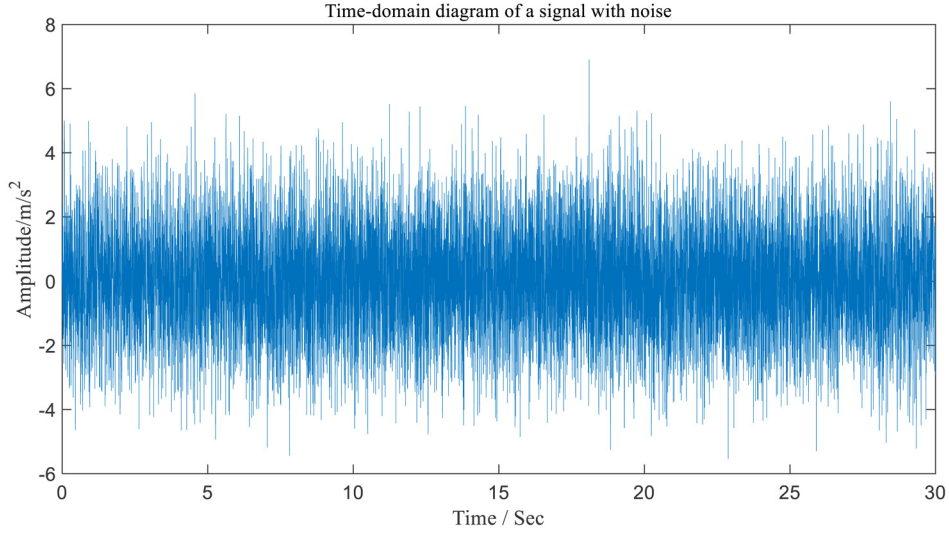


Fig. 2. Time-domain of simulation signal (SNR=0 dB).

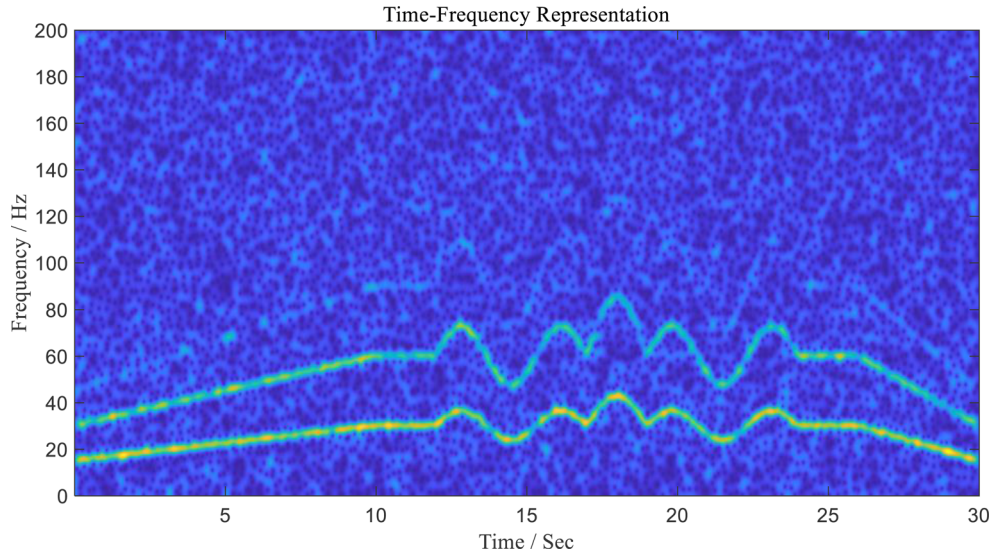


Fig. 3. Signal time-frequency diagram.

Using this instantaneous rotational frequency as the fundamental frequency, a simulated vibration signal $x(t)$ is constructed under the condition of large speed fluctuations in mechanical equipment, covering the second and third harmonics. The mathematical model is shown in equation (11). The sampling frequency is set to 400 Hz, $\eta(t)$ is Gaussian white noise set to 0 dB in the simulation verification. The simulated signal contains the fundamental frequency and its second and third harmonics. Finally, its time-domain waveform is shown in Figure 2.

$$x(t) = \sin\left(\int_0^t \omega \tau d\tau\right) + 0.8\sin\left(2\int_0^t \omega \tau d\tau\right) + 0.3\sin\left(3\int_0^t \omega \tau d\tau\right) + \eta(t). \quad (11)$$

Subsequently, the simulated signal $x(t)$ will be processed using the SET combined with the VKF. The proposed method is firstly applied to obtain the time-frequency

spectrum of original signal, as illustrated in Figure 3. The parameter required for SET is window function's length. In this paper, the window function length is set to 300. Following processing of the signal with SET, the result is obtained as shown in Figure 3.

Figure 3 illustrates a multi-component fast varying signal, which corresponds to the instantaneous rotating frequency component, second harmonic, and third harmonic components, respectively.

Given that the rotating frequency component exhibits the greatest energy in the simulated signal, we initially employ the ridge searching method to conduct a peak search on Figure 3, thereby extracting the instantaneous rotating frequency. Subsequently, the estimated rotating frequency and simulated signal are input into the Vold-Kalman filter (VKF) to extract the corresponding first-order component. Thereafter, the first-order component is subtracted from the

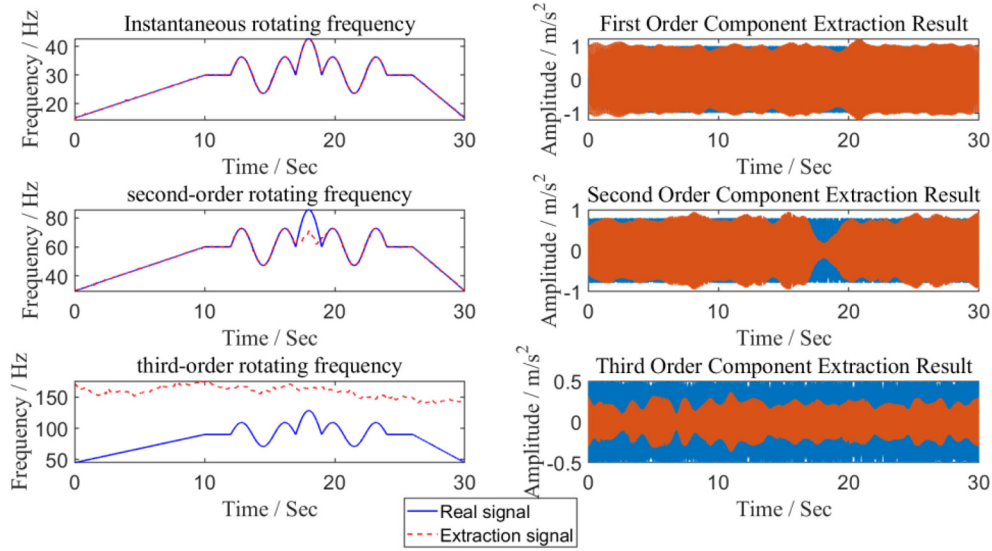


Fig. 4. Instantaneous frequency estimation and signal component extraction analysis.

original signal in order to obtain the residual signal. This process is repeated until all order components have been extracted.

Figure 4 illustrates the estimation results compared with original components. It is evident that the estimated first-order instantaneous frequency exhibits extremely high accuracy, the second-order instantaneous frequency extraction result is also quite precise, presenting fluctuation phenomenon only under extreme condition. While as for third-order instantaneous frequency, the extracted result fluctuates severely, leading to significant variations. Overall, the instantaneous frequencies of each order component are well estimated. Simultaneously, by using estimated instantaneous frequencies, we also extract a series of order components. As illustrated in Figure 4, the estimation results of first-order and second-order components are highly accurate. However, the extraction effect for the third-order component is not optimal. The reason for this situation is that its extraction efficiency of order components by using Vold-Kalman filter compactly depends on the estimated instantaneous frequencies.

To further demonstrate the proposed method's superiority, we select signal adaptive decomposition as comparative method for extracting first order component. We mainly adopt Empirical Mode Decomposition (EMD) and Variational Mode Decomposition (VMD) here, the advantage is it does not necessitate the specification of a predefined basis function, as shown in Figure 5.

Although it is easy to decompose mechanical vibration fault signal under large speed fluctuation condition, due to the intersect attribute of order components, the extraction results will present aliasing phenomenon. Finally, Table 1 also verifies the above conclusion from a quantitative perspective. In this paper, we select Mean Squared Error (MSE) and Pearson Product-Moment Correlation Coefficient r_{xy} to act as evaluation metrics and their formulas are given by equations (12) and (13), where x_i and y_i is the

true value, $\hat{y}_i$ is the predicted value, and N is the signal's length.

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (12)$$

$$r_{xy} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2}}. \quad (13)$$

As demonstrated in Table 1, the MSE value obtained through the proposed methodology is minimal, and the correlation coefficient is high, indicating a high degree of similarity between the extracted order components and the true order components. In contrast, the results obtained using Adaptive Chirp Mode Decomposition (ACMD) demonstrate that the combination of Kalman filtering and synchronous extraction has significant advantages in signal extraction. Additionally, the results of EMD and VMD also are compared, it indicates that the proposed method performs better in terms of accuracy and stability of signal extraction, further validating its effectiveness and reliability in handling complex signal.

In conclusion, as for a multi-order component signal, once the instantaneous frequencies have been determined, the VKF can be employed to extract correspondingly a series of order components. It can be seen that the EMD and VMD are vulnerable to interference on extracting order components in the presence of significant speed fluctuation, while the VKF exhibits excellent performance in signal component extraction. However, if the instantaneous frequency estimation is inaccurate, the results may be significantly affected. Therefore, the accuracy of the instantaneous frequency is crucial for precise order component extraction. To address the issue of insufficient instantaneous frequency extraction accuracy, more advanced instantaneous frequency estimation methods

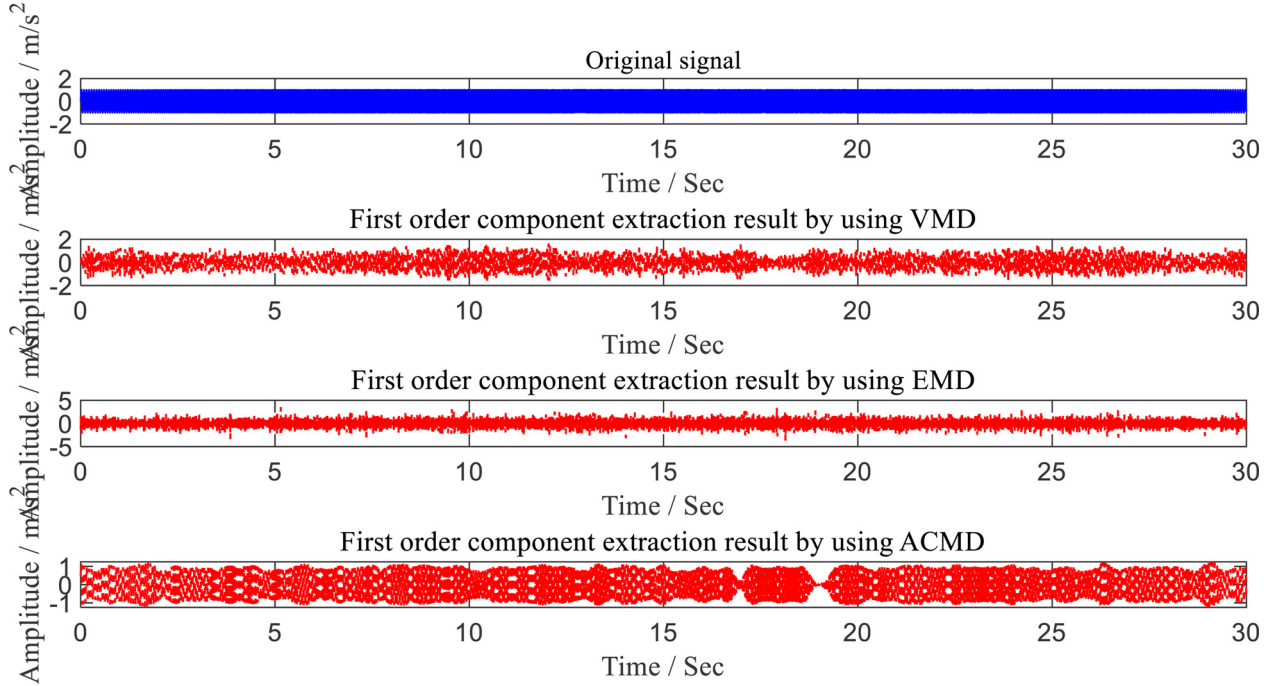


Fig. 5. First order-component extraction result by using comparison methods.

Table 1. Accuracy analysis comparison.

Input of component signal	$MSE(m/s^2)^2$	r_{xy}
This article uses the method of first order component	0.011	0.988
This article uses the method of second order component	0.044	0.929
This article uses the method of third order component	0.139	0.579
VMD first order component	0.154	0.832
VMD second order component	0.182	0.663
VMD third order component	0.183	0.021
EMD first order component	1.216	0.078
EMD second order component	0.569	0.416
EMD third order component	0.349	0.002
ACMD first order component	0.015	0.989
ACMD second order component	0.035	0.945
ACMD Third order component	0.108	0.337

can be considered to further improve the extraction accuracy of order components. This paper successfully achieves precise extraction of order components by applying the combined method of SET and VKF. Experimental results show that even in the presence of significant speed fluctuations, the SET-VKF method can accurately estimate instantaneous frequencies and extract clear and precise order component signals.

4.2 Anti noise and accuracy analysis

Furthermore, we analyze the noise resistance and estimation accuracy of the proposed method. Given that SET is crucial for achieving instantaneous frequency estimation, it

provides the time-frequency distribution of fault vibration signal. Time-frequency resolution is an important metric for evaluating the quality of time-frequency distribution. Here, we compare the methods using STFT and NLSTFT for time-frequency distribution. White noise is added to the aforementioned simulated signal, with the SNR varying from -10 dB to 10 dB. Rényi entropy is used as the evaluation metric, where a smaller Rényi entropy value indicates higher time-frequency resolution. Rényi entropy boasts powerful noise resistance, adaptability to non-stationary signals, and flexible parameter adjustment features, allowing for precise measurement of a signal's energy concentration on the time-frequency plane. By adjusting the order parameter α , Rényi entropy

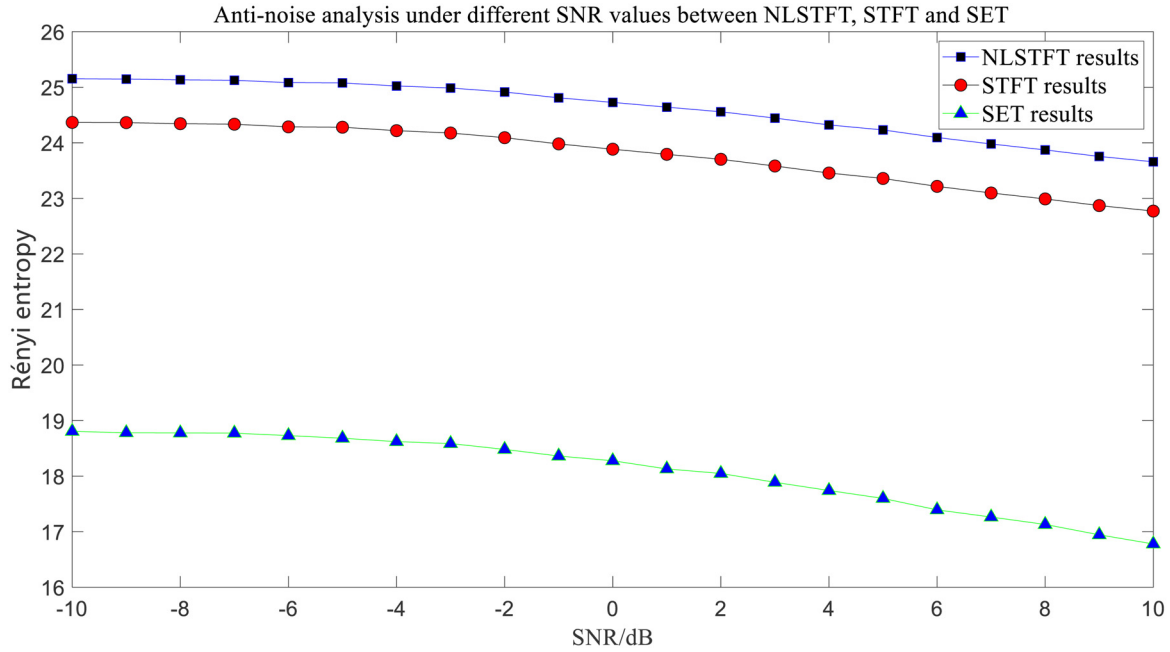


Fig. 6. Comparison of Rényi entropy under different signal-to-noise ratios.

Table 2. Comparison of error analysis.

Estimation method	Average relative error $\text{error}_{\text{avg}}$ (%)	Maximum relative error $\text{error}_{\text{max}}$ (Hr)
NLSTFT combination with ridge line searching	2.01	5.16
STFT combination with ridge line searching	2.79	6.14
proposed method	0.52	1.31

emphasizes the main characteristics of the signal and suppresses noise interference, making it particularly suitable for analyzing non-stationary signals in complex industrial environments. The analysis results are shown in Figure 5. The formulas for calculating SNR and Rényi entropy are given by equations (14) and (15).

$$\text{SNR} = 10 \log_{10} \left(\frac{P_s}{P_n} \right) \quad (14)$$

where P_s represents the signal's power and P_n represents the noise's power. A higher signal-to-noise ratio means that the signal is stronger relative to the noise.

$$H_\alpha(X) = \frac{1}{1-\alpha} \log \left(\sum_{i=1}^n p_i^\alpha \right) \quad (15)$$

where $\alpha > 0$ denotes the order of Rényi entropy, research shows that the value of α is 3, Rényi entropy can be a good measure of the signal's time-frequency distribution.

As shown in Figure 6, the Rényi entropy of SET is lower than the STFT and NLSTFT. With the SNR's increase, the Rényi entropy of SET gradually decreases with a smaller variation range, indicating that the time-frequency

resolution of SET is less affected by SNR. SET maintains high time-frequency resolution under different SNR condition, demonstrating strong robustness to noise. The small variation in Rényi entropy with varying SNR indicates stable performance, less influenced by changing external environment, confirming that estimating instantaneous frequency based on SET's time-frequency distribution is a correct choice.

Additionally, as shown in Table 2, the average relative error $\text{error}_{\text{avg}}$ and maximum relative error $\text{error}_{\text{max}}$ of instantaneous frequency processed by SET are smaller than STFT and NLSTFT, indicating the practical significance of using SET's time-frequency distribution. Besides, the formulas corresponding to $\text{error}_{\text{avg}}$ and $\text{error}_{\text{max}}$ are shown in following, where N is the length of signal, $f_{r,i}$ is the i -th sample point of true frequency, and $f_{e,i}$ is the i -th sample point of estimated frequency.

$$\text{error}_{\text{avg}} = \frac{1}{N} \sum_{i=1}^N \left| \frac{f_{r,i} - f_{e,i}}{f_{r,i}} \right| \quad (16)$$

$$\text{error}_{\text{max}} = \max(|f_{r,i} - f_{e,i}|). \quad (17)$$

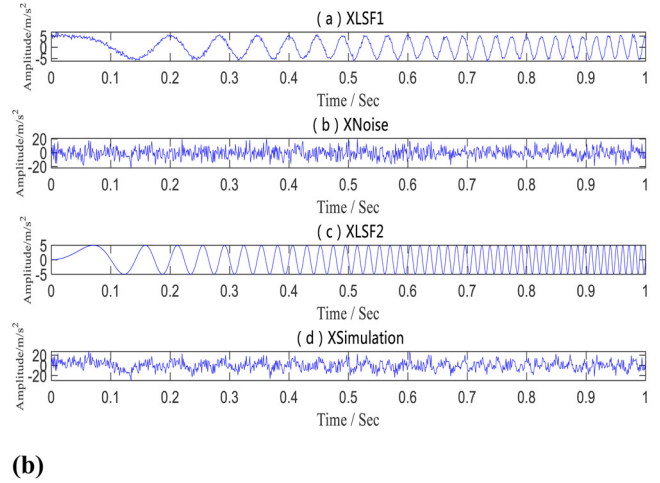
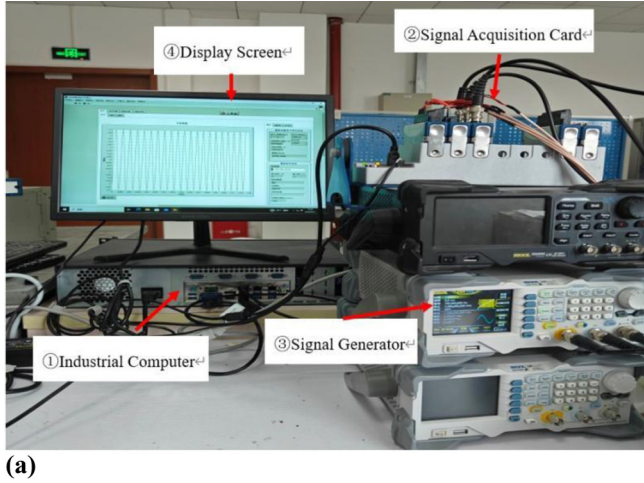


Fig. 7. (a) Semi-physical validation Platform. (b) Time domain of validation signal $X_{Simulation}$.

In general, the average relative error $error_{avg}$ is mainly used to evaluate the overall performance of the model. A lower average relative error indicates that the model can accurately estimate the instantaneous rotational frequency in most cases, demonstrating good overall performance. The maximum relative error $error_{max}$ is mainly used to evaluate the model's performance under extreme conditions. A lower maximum relative error indicates that the model does not produce large errors under any circumstances, demonstrating good robustness and reliability.

The SET enhances signal localization accuracy by redistributing energy on the time-frequency plane. It concentrates energy onto the signal's instantaneous frequencies, improving the estimation precision of these frequencies, especially in cases of rapidly changing frequencies. Even in noisy environments, SET maintains high time and frequency resolution, accurately distinguishing different frequency components. This capability provides precise data support for equipment fault diagnosis and predictive maintenance.

5 Experimental validation

5.1 Semi-physical simulation

In this section, we use the simulation signal generated by the dynamic signal processing system built in the laboratory for semi-physical verification. The experimental system consists of a dual-channel signal generator of Puyuan DG1032, a dynamic vibration signal acquisition card, and an industrial computer, as shown in Figure 7a. A signal generator is used to generate a linear swept component X_{LSF1} , which has an amplitude of 5 m/s^2 and its IF varies from 0 Hz to 50 Hz conforming to linearly increasing law, with a sampling frequency of 1000Hz, while another signal generator is used to simulate a noise component X_{Noise} . Finally, we use Matlab to generate another linear swept component X_{LSF2} which has an amplitude of 5 m/s^2 , and its IF varies from 0 Hz to 100 Hz conforming to linearly increasing law. The above three

components are superimposed to obtain the validation signal $X_{Simulation}$. Further, the validation signal $X_{Simulation}$ is captured by using the dynamic signal acquisition card and displays on the interface by using LabView as shown in Figure 7b.

Finally, we use the proposed model to extract the IF corresponding to order components X_{LSF1} and X_{LSF2} respectively, as shown in Figures 8a and 8b. It can be observed that the extracted IF closely align with the actual frequency, indicating that the estimation method has high accuracy.

Using the two estimation IFs, the corresponding order components $X_{Extracted-LSF1}$ and $X_{Extracted-LSF2}$ can also be extracted as shown in Figures 8 and Figure 8d, it also presents the comparison between extracted order components and real order components X_{LSF1} and X_{LSF2} that they are generally consistent.

Furthermore, we quantitatively analyze the similarity between the extracted order components and original order components, here, we also select two indicators which are mean squared error MSE, correlation coefficient r_{xy} , and the result is shown in Table 3. In general, the correlation coefficients are relatively all close to 1, indicating that the extraction results are accurate. Therefore, the proposed method is suitable for signal decomposition under varying speed condition.

5.2 Rolling bearing fault vibration signal experimental validation under varying speed condition

We use the rolling bearing vibration test signal under variable speed condition from Xi'an Jiao tong University, the experiment uses the SQ (Spectra Quest) company's mechanical failure comprehensive simulation test bench to simulate the motor bearing outer ring and inner ring failure. The structure of the test bench is shown in Figure 9, the test bench consists of motor, rotor and load, the experiment uses piezoelectric acceleration sensors to collect motor bearing vibration signal, the data acquisition instrument used is CoCo80, the sampling frequency is 25.6KHz. The style of motor bearing is NSK6203.

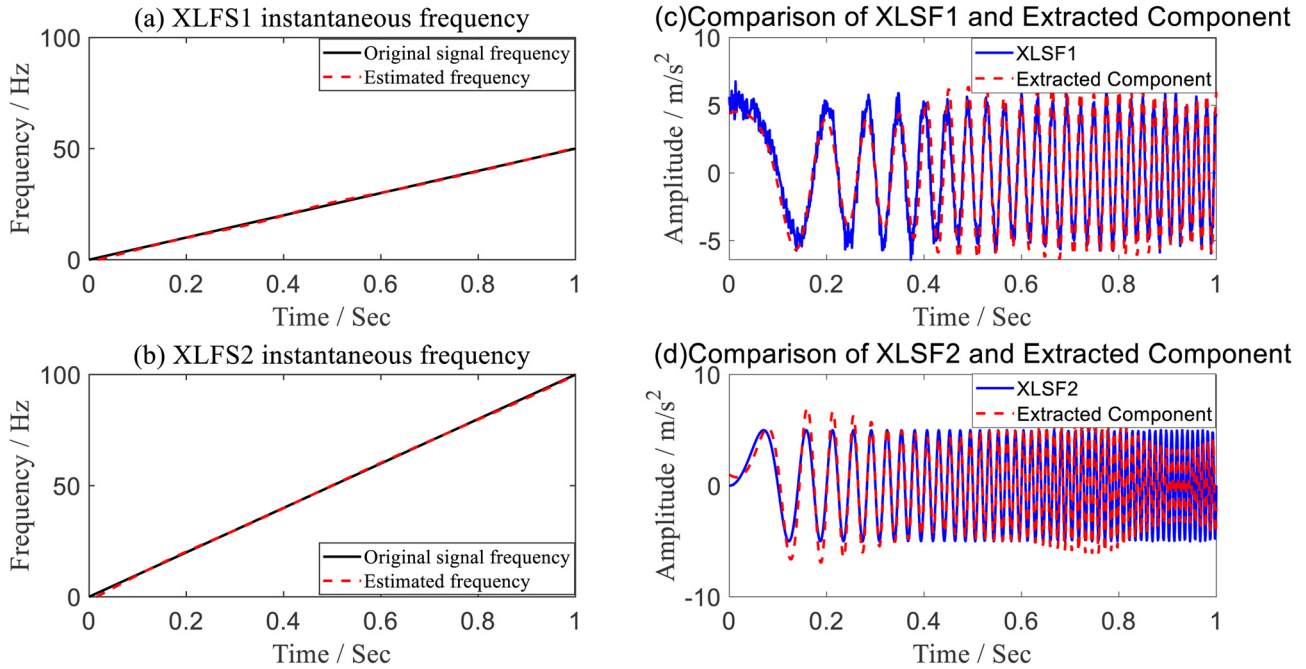


Fig. 8. Instantaneous frequency estimation and order component extraction corresponding to validation signal $X_{Simulation}$.

Table 3. Comparison of accuracy analysis.

Order component	$MSE(m/s^2)$	r_{xy}
X_{LSF1}	1.33	0.96
X_{LSF2}	0.87	0.97

The “NC-REC3642-ch2.” is designated as experimental validation signal whose speed conforms to linear varying law, as original signal has a high sampling frequency and large number of sampling points, it is a challenge for direct time-frequency analysis that will lead to a series of issues such as insufficient memory and a low computation efficiency. In order to address this problem, it is essential to down-sample experimental signal initially, with a down-sampling factor of 50. Finally, the corresponding rolling bearing fault vibration signal is depicted in Figure 10.

Furthermore, Figure 11a shows the instantaneous rotational speed extracted according to the proposed model, which includes the instantaneous first, second, third, and fourth rotating frequencies. Figure 11b shows a comparison between the estimated rotational frequency without a tachometer and the estimation based on key phase pulse signals. Obviously, it is evident that the estimation result by the proposed model successfully captures a complete acceleration and deceleration process. Specifically, it starts from a stationary state, gradually accelerates, maintains stability, and eventually decelerates. The original data indicates that the rotating speed remains stable state after accelerating to 3000 rpm, which corresponds to 50 Hz ($3000/60 = 50$ Hz). From Figure 11b, it is apparent that during the time interval from 4s to 14s, the estimated rotating frequency aligns with the true

rotating frequency, effectively reflects the actual rotating speed’s varying law. Considering the vibration signal undoubtedly contains noise, the estimation result presents some fluctuations in the beginning and end stages.

Finally, we sequentially estimated the remaining instantaneous frequencies and extracted corresponding order components, residual component, as shown in Figures 11c and 11d.

In conclusion, when we employ the proposed model to estimate IRF and extract a series of order components in the context of multi-component coupling fault diagnosis application, it not only yields an accurate estimation result but also facilitates the rapid and efficient identification. Consequently, the proposed method can be utilized where it is not possible to place an encoder to achieve rotating speed measurement.

6 System implementation

The system design is comprised of two distinct categories: hardware and software. The former includes the physical components, while the latter encompasses the logical components. The system design is further divided into three modules: data generation, data acquisition, and data processing.

The overarching system structure is illustrated in Figure 12. Due to the limitations of the experimental environment, a semi-physical simulation platform was constructed to simulate the vibration signal collected in an industrial setting. This platform comprises an NIcDAQ-9174 data acquisition module and a control terminal industrial computer. The data acquisition module incorporates four distinct types of data acquisition cards: NI 9215, NI 9375, NI 9232, and NI 9230.

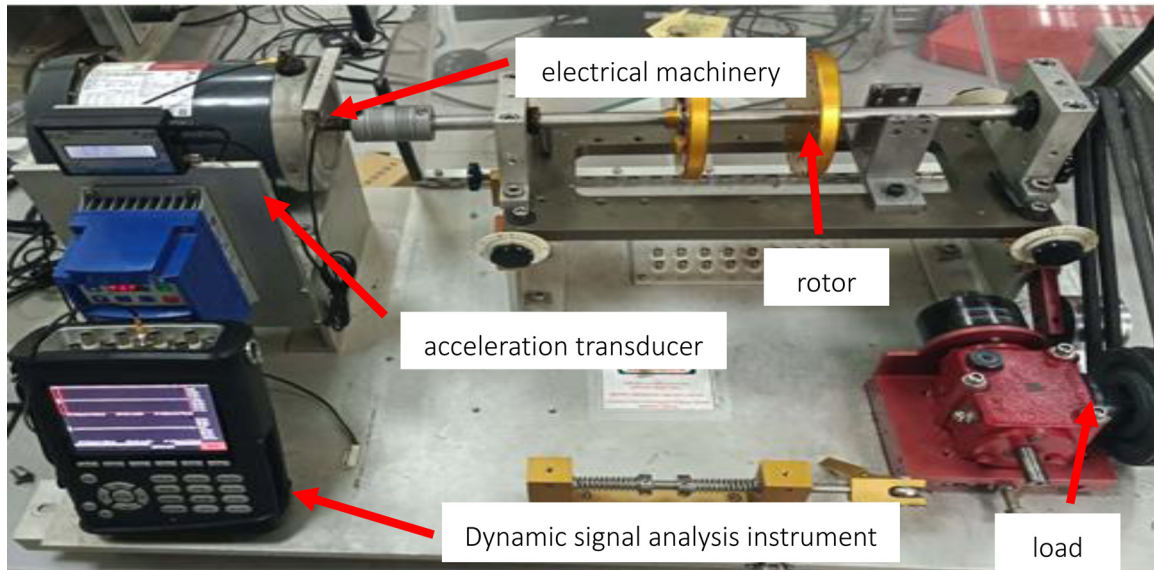


Fig. 9. Rolling bearing test bench under varying speed condition.

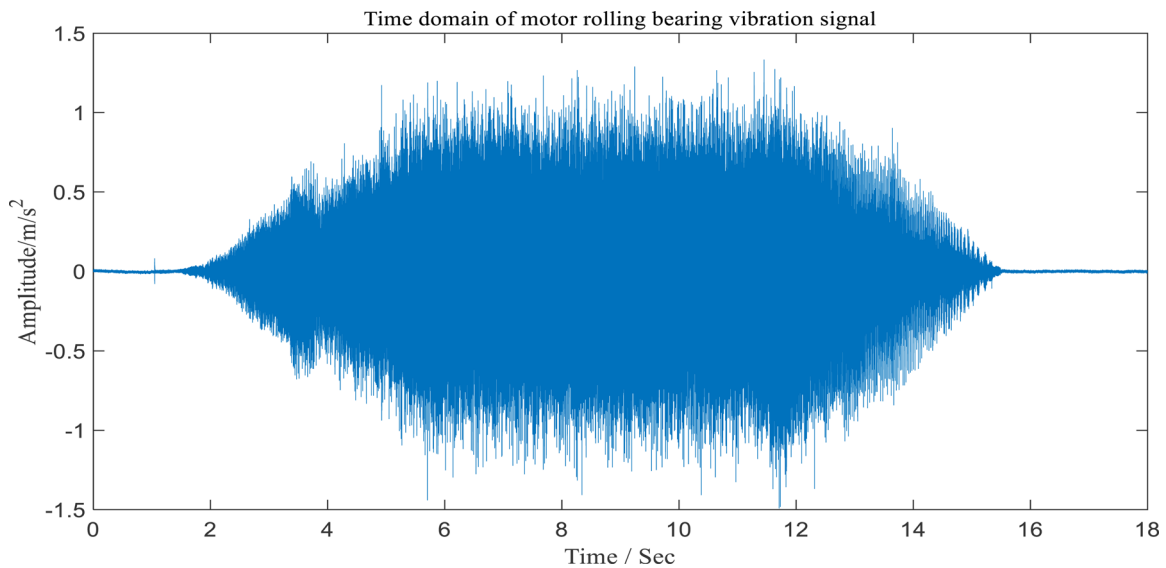


Fig. 10. Time domain of motor rolling bearing vibration signal.

When the fault vibration signal is input into the acquisition module through the data acquisition cards, with parameters such as sampling frequency being set accordingly. Upon receipt of the data, the system is then able to perform real-time signal acquisition, reading and writing functions on the interface, and save the collected signals in TDMS file format. The main functions of the system are shown in [Figure 13](#).

As for system software design, when the hardware connections have been completed, the software is initiated in order to set parameters such as system hardware and sampling information. When operating in online acquisition mode, the window displays real-time vibration signal. Once data has been successfully acquired, data analysis commences. In accordance with

user requirements, raw data and analysis results can be saved. The system functions include plotting raw signal waveform, time-frequency spectrogram, spindle speed plots, order component extraction and accuracy analysis, and data management.

The signal acquisition interface is responsible for acquiring signal. This module is for the configuration of parameters related to signal acquisition, including input channels, terminal configurations, sampling frequency, and the number of sampling points required for the acquisition of vibration signal. The specific steps are as follows. Prior to acquiring signal, it is necessary to set the relevant parameters of the sampling module in accordance with the specific experimental requirement. This entails setting parameters such as the sampling frequency and the number

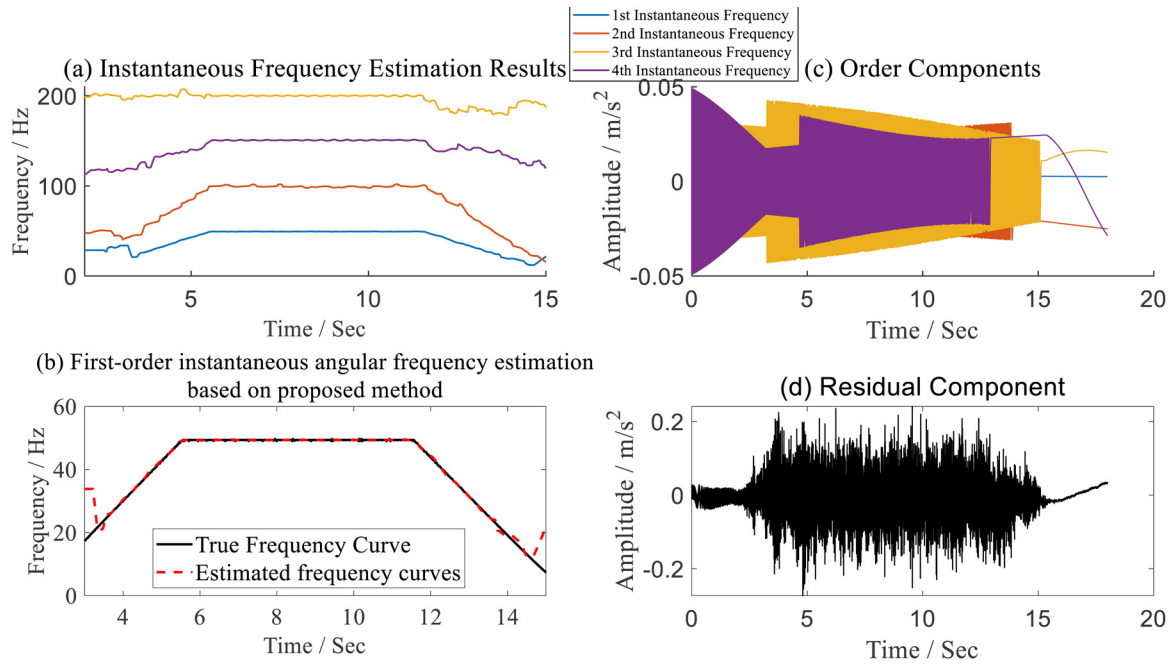


Fig. 11. Instantaneous frequency extraction results and a series of extracted order components and residual component.

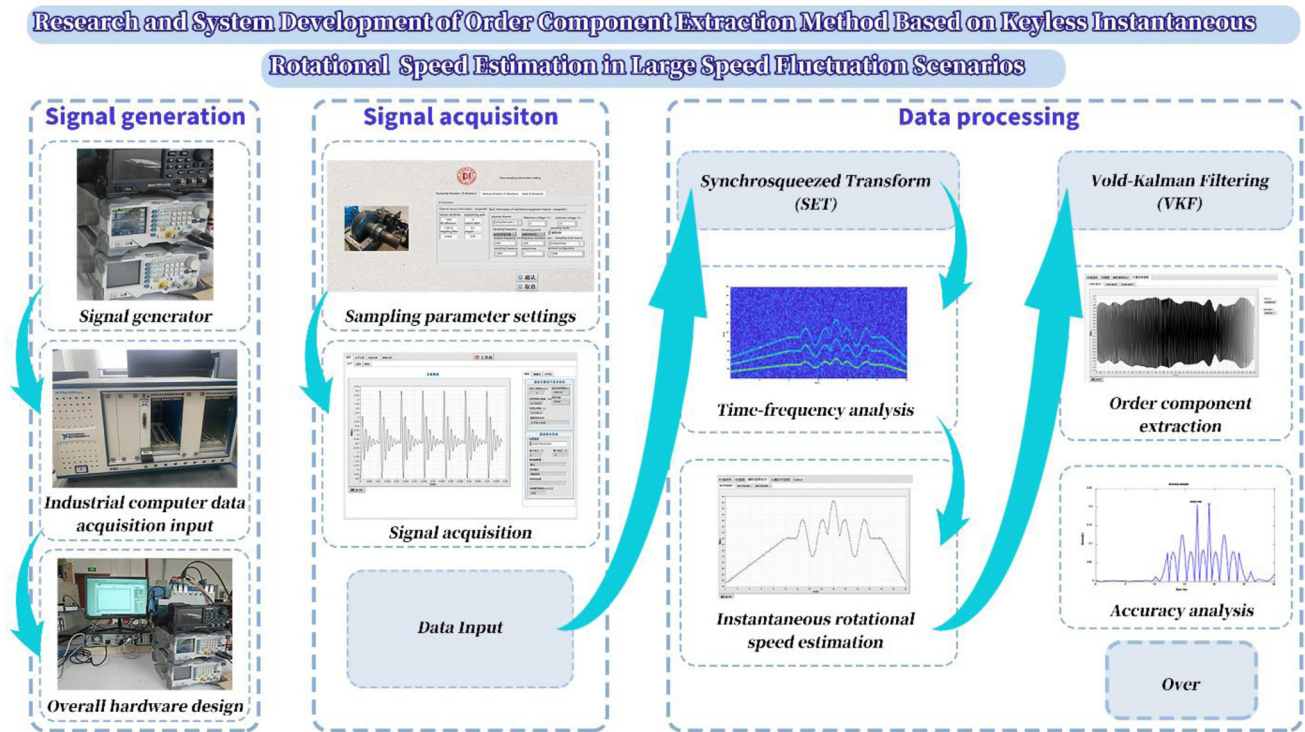


Fig. 12. System operation flow chart.

of physical channels. Once this has been completed, the “Confirm” button should be clicked in order to achieve vibration signal acquisition. The front panel is illustrated in Figure 14a, while the acquisition interface is shown in Figure 14b.

The proposed algorithm is implemented through MATLAB scripts, which display the processing results by setting variables and display controls. By processing the signal in accordance with the methodologies delineated in Section 2, the instantaneous frequencies and first, second,

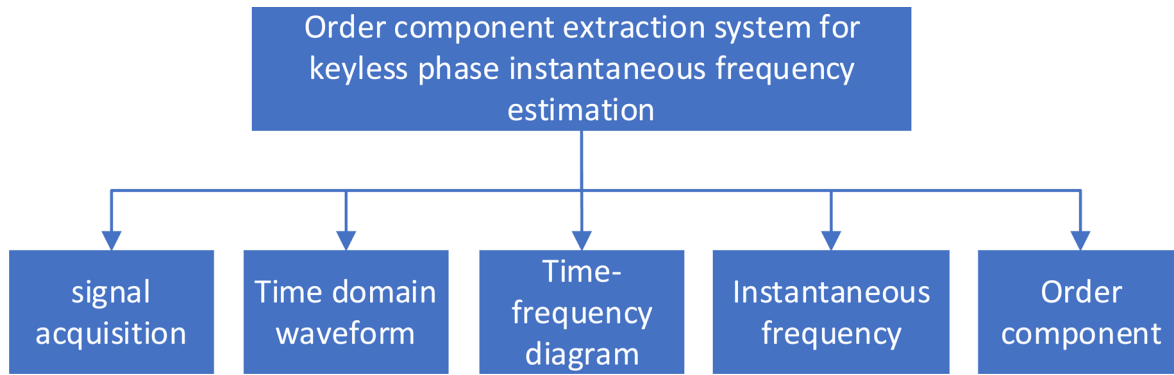


Fig. 13. Main functions of the system.

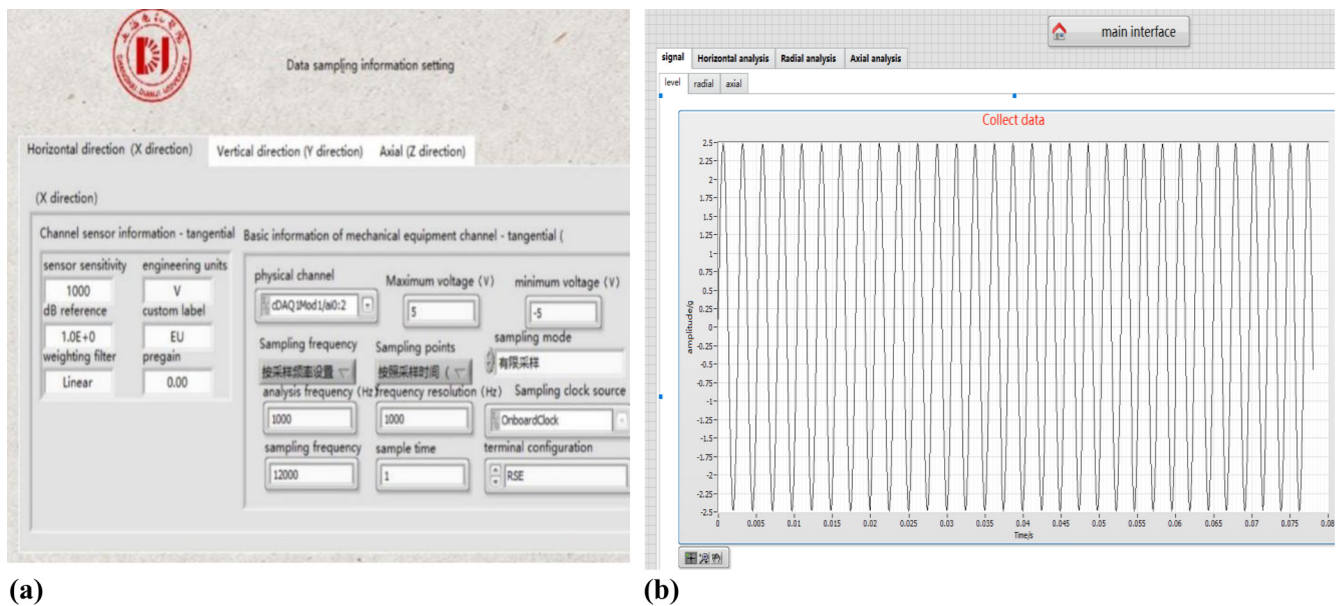


Fig. 14. (a) Signal acquisition setting. (b) Signal acquisition interface.

and third order components can be obtained. Figure 15 illustrates the instantaneous rotating frequency, which clearly demonstrates the extraction effect. Figure 16 depicts the first order component's extraction effect, with an MSE of 0.009 and a correlation coefficient of 0.99. Both of these values indicate high accuracy and demonstrate the effectiveness of the model.

In conclusion, this system has devised and its hardware components comprise an NI cDAQ-9174 data acquisition module, and the associated data acquisition cards. The software component combines the LabVIEW and MATLAB platforms to construct a robust data acquisition and processing system. The system employs LabVIEW for data acquisition, storage, and parameter settings, while MATLAB script nodes are used for complex algorithm calculations and displaying result. Experimental results demonstrate that the system can effectively extract the instantaneous frequencies and order components with high accuracy, which has significant engineering application value.

7 Conclusion

In general, PdM is an important component of the smart factory, as smart factory's equipment works under a larger speed fluctuation condition, its condition signal possesses significantly non-stationary property, exhibits rapidly varying instantaneous frequencies with multi-component, the PdM should cover a order component extraction part. When we use the conventional time-frequency analysis techniques, such as the nonlinear short-time Fourier transform, tend to exhibit reduced accuracy under a larger speed fluctuation condition. Consequently, we introduce Synchronous Extractive Transform (SET) to extract fast-varying rotational frequency from fault vibration signal results in higher accuracy, and furthermore, propose a SET-VKF tachometer-less order tracking method. Simulation and rolling bearing fault vibration signal prove the proposed method's efficiency. Finally, the following conclusions are drawn.

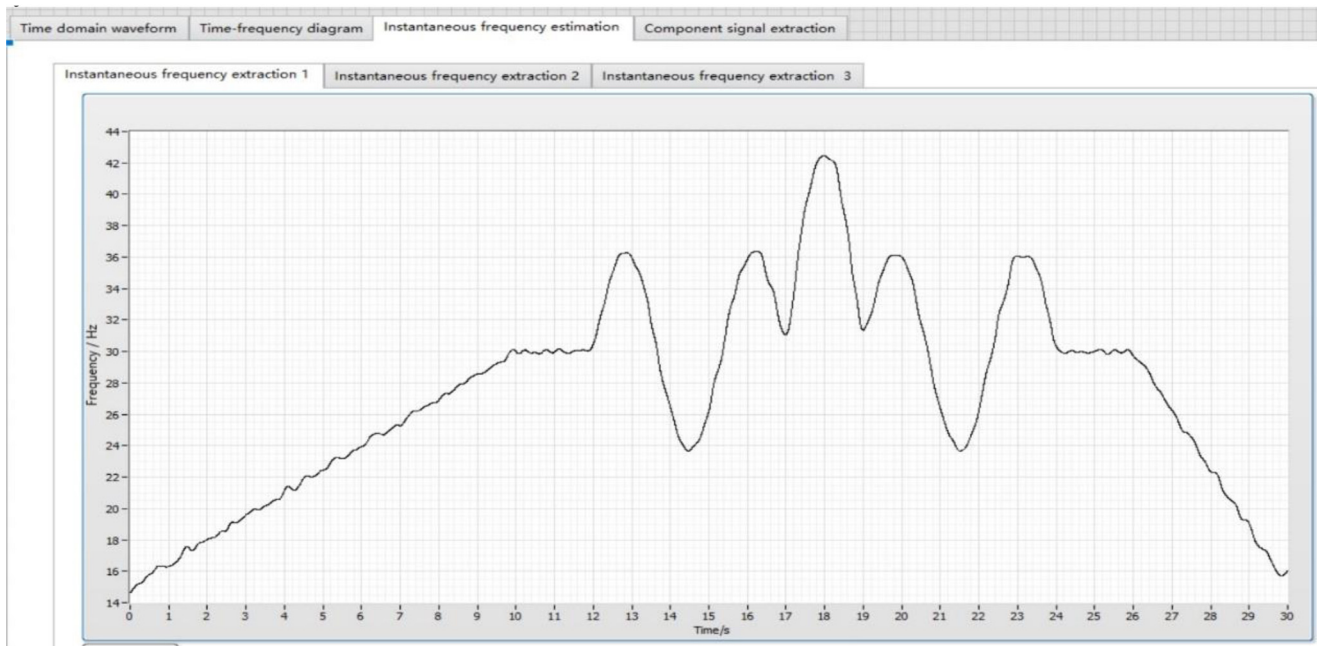


Fig. 15. Display of instantaneous rotating frequency.

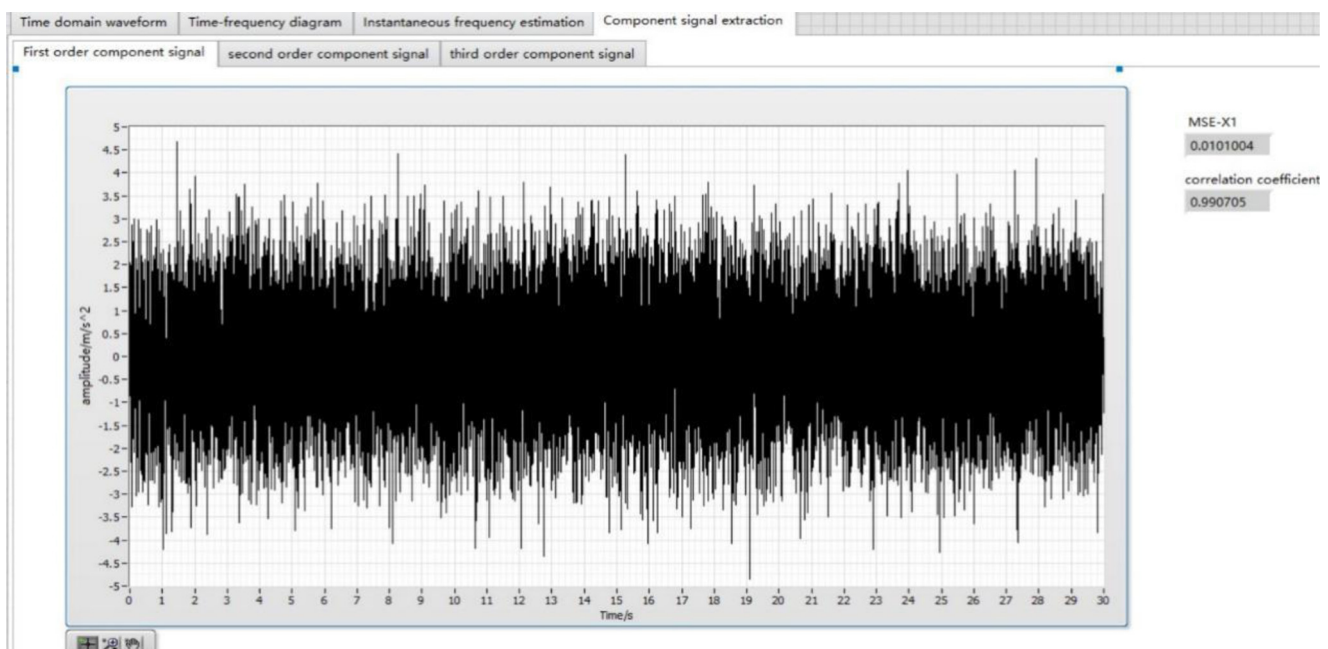


Fig. 16. Display of order component extraction.

- This paper introduces a methodology for the order components extraction based on Kalman filtering and the Synchronous Extractive Transform (SET). Firstly, the condition signal's time-frequency spectrogram is constructed using SET, and then the ridge peak searching method is employed to estimate the instantaneous rotational frequency whose corresponding order component has the highest energy that has been proved to have a high-precision estimation. On this basis, combining the

Kalman filtering, it also allows to extract corresponding order component, providing an effective solution for handling fault vibration signal under a large speed fluctuation condition. This high-precision component extraction and fault diagnosis have laid a solid foundation for predictive maintenance. By introducing predictive maintenance, intelligent factories can monitor equipment status in real time, identify potential faults in advance, and ensure efficient operation of equipment.

- The proposed method has been incorporated into LabVIEW, resulting in the development of an order component extraction system with tangible engineering application. The system is comprised of two principal modules: a signal acquisition module, and a signal processing module. A user-friendly interface has been developed in LabVIEW for the real-time monitoring and control of the signal acquisition process. The signal acquisition module employs high-speed data acquisition cards to transfer the vibration signal collected by sensors into the computer. The signal processing module utilizes MATLAB's robust computational capabilities to process and analyse the acquired signal. By invoking MATLAB scripts and functions, the system can estimate instantaneous frequencies and extract order components. Experimental results demonstrate that the system has a prospective applications and value.
- In the future, the proposed method can be combined with traditional demodulation techniques to create a keyless amplitude-phase demodulation technique. This provides an effective means for diagnosing faults in mechanical equipment under variable working conditions without the use of tachometer. Furthermore, considering the SET has unavoidable shortage on processing high amount of data, and it brings considerable blurring phenomenon in time-frequency spectrum, it is necessary to investigate a more accurate time-frequency distribution technique with a view to enhance the condition's energy concentration.

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Conflicts of interest

The author(s) declared no potential conflicts of interest with respect to the research, author-ship, and/or publication of this article.

Data availability statement

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Author contribution statement

All Author is contributed to the design and methodology of this study, the assessment of the outcomes and the writing of the Manuscript.

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