

VIBRATION FEATURE EXTRACTION METHODS FOR GEAR FAULTS DIAGNOSIS - A REVIEW

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Abstract. *The key point of condition monitoring and fault diagnosis of gearboxes is a fault feature extraction. The study of fault feature detection in rotating machinery from vibration analysis and diagnosis has attracted sustained attention during the past decades. In most cases, determination of the condition of a gearbox requires the study of more than one feature or a combination of several techniques. This paper attempts to survey and summarize the recent research and development of feature extraction methods for gear fault diagnosis, providing references for researchers dealing with this topic and helping them identify further research topics. First, the feature extraction methods for gear faults diagnosis are briefly introduced, the usefulness of the method is illustrated and the problems and the corresponding solutions are listed. Then, recent applications of feature extraction methods for gear faults diagnosis are summarized, in terms of industrial gearboxes. Finally, the open problems of feature extraction methods for gear fault diagnosis are discussed and potential future research directions are identified. It is expected that this review will serve as an introduction summary of vibration feature extraction methods for gear faults diagnosis for those new to the concepts of its applications to gear fault diagnosis based on vibration.*

Key words: vibration, gearbox, feature extraction

1. INTRODUCTION

Vibration diagnosis is the most commonly used technique to monitor the condition of gearboxes. Gearbox is one of the core components in rotating machinery and has been widely employed in various industrial equipments. Faults occurring in gearbox, such as gears and bearings defects, must be detected as early as possible to avoid fatal breakdowns of machines and prevent loss of production and human casualties. Vibration

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signal collected from these equipments during operation contains valuable information about the condition of machine condition. The vibration signal is often a complex signal which contains stationary, non-stationary and noisy components. Therefore, the information for maintenance decisions is not readily available from these vibration data unless the appropriate signal processing techniques are chosen [1]. Different fault diagnosis methods have been developed and used to detect and diagnose gear faults. One of the principal tools for diagnosing gear faults is the vibration based analysis because of the ease of vibration measurements [2,3]. By employing the appropriate data analysis algorithms, it is possible to detect the changes in vibration signals caused by fault components, and to make decisions about the gearboxes health status [4] and gear fault evaluation. Feature extraction is a mapping process from the measured signal space to the feature space. Representative features associated with the conditions of machinery components should be extracted by using appropriate signal processing and calculating approaches [4]. Over the past few years, various techniques including Fourier transform (FT), envelope analysis (EA), wavelet transform (WT) and some other time frequency distributions were employed to processing the vibration signals [5, 6]. Based on these processing techniques, statistic calculation methods, autoregressive model (AR), singular value decomposition (SVD), principal component analysis (PCA) and independent component analysis (ICA) have been adopted to extracting representative features for machinery fault diagnosis [7]. Even though several techniques have been proposed in the literature for feature extraction, it is still a challenge in implementing a diagnostic tool for real-world monitoring applications because of the complexity of machinery structures and operating conditions. This paper attempts to summarize and review the recent research and development of feature extraction methods in fault diagnosis of gear faults. It aims to synthesize and place the individual pieces of information on this topic in context and provide references for researchers, helping them develop advanced research in this area.

2. FEATURE EXTRACTION

2.1. Time domain feature extraction

The time domain signal collected from a gearbox usually changes when damage occurs in a gear. Both amplitude and content may be different from those of the time domain signal of a normal gear. Root mean square reflects the vibration amplitude and energy in time domain. Standard deviation, kurtosis, crest factor and shape factor may be used to represent the time series distribution of the signal in the time domain. First, five time-domain features, namely, standard deviation, root mean square, kurtosis, crest factor and shape factor, are calculated. They are defined as follows [8]:

(1) Standard deviation (STD)

$$\text{STD} = \sqrt{\frac{1}{(n-1)} \sum_{i=1}^n (x_i - \bar{x})^2} \quad (1)$$

where x_i ($i=1, \dots, n$) is i th sampling point of the signal x ; n is the number of points in the signal, and \bar{x} is the average of the signal.

(2) Root mean square (RMS)

$$\text{RMS} = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_i)^2} \quad (2)$$

(3) Kurtosis (KR)

$$\text{KR} = \frac{n \sum_{i=1}^n (x_i - \bar{x})^4}{\left(\sum_{i=1}^n (x_i - \bar{x})^2 \right)^2} \quad (3)$$

(4) Crest factor (CF)

$$\text{CF} = \frac{\max |x_i|}{\sqrt{\frac{1}{n} \sum_{i=1}^n (x_i)^2}} \quad (4)$$

(5) Shape factor (SF)

$$\text{SF} = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (x_i)^2}}{\frac{1}{n} \sum_{i=1}^n |x_i|} \quad (5)$$

Despite traditional time domain signal analysis, advanced methods of gearbox vibration analysis deal with 5 different forms of vibration time waveforms: raw signal, time synchronized and averaged signal, residual signal, differential signal, bandpass filtered timewave – filtered around gearmesh frequency (Fig 1).

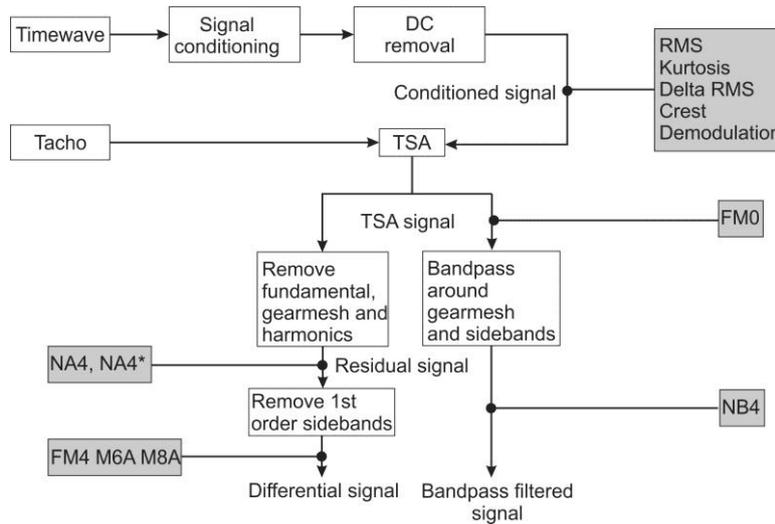


Fig. 1 Algorithm for calculating different time domain features for gearbox failures detection

Time Synchronous Averaging (TSA) is a fundamentally different process than the usual spectrum averaging that is generally used in FT analysis. While the concept is similar, TSA results in a time domain signal with lower noise than in a case of a single sample. A FT can then be computed from the averaged time signal. The signal is sampled using a trigger that is synchronized with the signal. The averaging process gradually eliminates random noise because the random noise is not synchronous with the trigger signal. Only the signal that is synchronous and coherent with the trigger will persist in the averaged calculation. With TSA the result is a time domain signal with very low noise because the averaging is performed in the time domain and not in the frequency domain. In addition, it is possible to compute the FT of the averaged time signal resulting in a spectrum with low noise. When time domain averaging is computed on a vibration signal from a real machine, the averaged time record gradually accumulates the components of the signal that are synchronized with the trigger. Other components of the signal, such as noise and components from rotating parts of the machine are effectively averaged out. This is the only type of averaging that actually does reduce noise in the time domain. Another important application of time synchronous averaging is in the waveform analysis of machine vibration, especially in the case of gear drives. In this case, the trigger is derived from the tachometer that provides one pulse per revolution of a gear in the machine. This way, the time samples are synchronized in that they all begin at the same exact point related to the angular position of the gear. After performing a sufficient number of averages, spectrum peaks that are harmonics of the gear rotating speed will remain while non-synchronous peaks will be averaged out from the spectrum. As a typical feature of the time synchronized signal, the above mentioned parameters are used as well as another one, FM0 parameter. FM0 is defined as

(6) FM0

$$FM0 = \frac{PP_x}{\sum_{h=0}^H P_h} \quad (6)$$

where PP_x is the maximum peak-to-peak value of signal x , P_h is the amplitude of the h th harmonic of the meshing frequency, and H is the total number of harmonics considered.

After processing (Fig. 1) other features are defined also:

(7) FM4

$$FM4 = \frac{n \sum_{i=1}^n (d_i - \bar{d})^4}{\left(\sum_{i=1}^n (d_i - \bar{d})^2 \right)^2} \quad (7)$$

where d_i is the i th measurement of the difference signal of the signal x and \bar{d} is the average of the difference signal. The shaft frequencies and their harmonics, the meshing frequencies and their harmonics, and all first-order sidebands are defined to be the regular meshing components. By removing the regular meshing components from signal x , the so

called difference signal is generated. FM4 is actually the kurtosis of the difference signal. It is designed to complement FM0 by detecting damage isolated to only a limited number of teeth and supposed to work well for detection of initial faults.

(8) NA4

$$\text{NA4} = \frac{\frac{1}{n} \sum_{i=1}^n (r_i - \bar{r})^4}{\left(\frac{1}{N} \sum_{j=1}^N \left(\frac{1}{n} \sum_{k=1}^n (r_{jk} - \bar{r}_j)^2 \right) \right)^2} \quad (8)$$

where r_i is the i th measurement of the residual signal of time record x_i and \bar{r} is the average of r_i , r_{jk} is the k th measurement in the j th time record residual signal r_j , \bar{r}_j is the average of r_j , and N is the number of time records in a run ensemble. The complete data series collected is called a run ensemble. It is further divided into N time records each including n data points. The residual signal is generated by removing the regular meshing elements which include the shaft frequencies and their harmonics, and the meshing frequencies and their harmonics. NA4 is created to overcome the shortcoming of FM4 that becomes less sensitive to the progression of fault in both number and severity. For this reason, it is supposed to be able to not only detect the onset of fault, as FM4 does, but also continue to react to the damage as it spreads and increases in magnitude.

(9) NB4

$$\text{NB4} = \frac{\frac{1}{n} \sum_{i=1}^n (s_i - \bar{s})^4}{\left(\frac{1}{N} \sum_{j=1}^N \left(\frac{1}{n} \sum_{k=1}^n (s_{jk} - \bar{s}_j)^2 \right) \right)^2} \quad (9)$$

where s_{jk} is the k th measurement in the j th time record envelope s_j ; \bar{s}_j is the average of s_j , and N is the number of time records in a run ensemble. The theory behind NB4 is that the damage on gear teeth will cause transient load fluctuation that is different from that caused by normal teeth, and that this can be seen in the envelope of the signal.

(10) Energy ratio (ER)

$$\text{ER} = \sqrt{\frac{\frac{1}{n} \sum_{i=1}^n (d_i)^2}{\frac{1}{n} \sum_{i=1}^n (d'_i)^2}} \quad (10)$$

where d_i is the i th measurement of the difference signal, and d'_i is the i th measurement of the regular meshing components, which include the shaft frequencies and their harmonics, the meshing frequencies and their harmonics, and all first-order sidebands. ER is defined as the ratio of the root mean squares between the difference signal and the signal containing only regular meshing components.

(11) Energy operator (EOP)

$$\text{EOP} = \frac{n \sum_{i=1}^n (re_i - \overline{re})^4}{\left(\sum_{i=1}^n (re_i - \overline{re})^2 \right)^2} \quad (11)$$

where re_i is the i th measurement of the resulting signal re , and \overline{re} is the average of the resulting signal. The energy operator is then computed by taking the kurtosis of the resulting signal.

2.2. Frequency domain feature extraction

Four frequency-domain feature parameters are extracted from the frequency spectrum of a gear vibration signal in this work. These frequency domain parameters may contain information that is not present in the time domain feature parameters. They are defined as follows[9]:

(12) Mean frequency (MF)

$$\text{MF} = \frac{1}{K} \sum_{k=1}^K X_k \quad (12)$$

where X_k is the k th measurement of the frequency spectrum of signal x and K is the total number of spectrum lines.

(13) Frequency center (FC)

$$\text{FC} = \frac{\sum_{k=1}^K f_k X_k}{\sum_{k=1}^K X_k} \quad (13)$$

where f_k is the frequency value of the k th spectrum line and X_k is the k th measurement of the frequency spectrum.

(14) Root mean square frequency (RMSF)

$$\text{RMSF} = \sqrt{\frac{\sum_{k=1}^K f_k^2 X_k}{\sum_{k=1}^K X_k}} \quad (14)$$

(15) Standard deviation frequency (STDF)

$$\text{STDF} = \sqrt{\frac{\sum_{k=1}^K (f_k - \text{FC})^2 X_k}{\sum_{k=1}^K X_k}} \quad (15)$$

MF indicates the vibration energy in the frequency domain. FC and $RMSF$ show the position changes of the main frequencies. $STDF$ describes the convergence degree of the spectrum power.

2.3. Time - frequency domain feature extraction

In Sections 2.1 and 2.2, the time and frequency-domain features are extracted from the vibration signals, respectively. In order to acquire additional characteristic information of gear damage, advanced signal processing techniques are used. Gearboxes often operate under some small fluctuation around nominal load/speed conditions during their normal service. These fluctuations result in a variation of both the modulations and their carrier frequencies (gear mesh harmonics) that blurs the sideband components in the spectra of the vibration measurement, often making it difficult to be recognized [10]. Such smearing effect can be abated by the order tracking technique or the time synchronous averaging (TSA) that acquires the measurements synchronized at identical angle increment instead of the identical sampling period. Although TSA is a well-established technique for analyzing gearbox vibration signals, its commercial implementation is limited because of the requirement for additional shaft mounted encoders to provide a measure of shaft angular position and sophisticated interpolation algorithms to resample the vibration data. Since such equipment and resources lead to increased cost to applications, they are usually absent in most industrial applications. In such cases, the conventional method is to extract the measurement over a shorter time duration using a sliding window during which the gearbox is presumed to operate under stationary condition. However, these shorter length vibration signals are usually analyzed using Fourier transforms that has limitations such as the limited frequency resolution and spectral leakage, while the small operational speed oscillations continue to exist [11]. To avoid the extra cost incurred in implementation of TSA and shortcomings of the Fourier transform based analysis, a time domain methods wavelet transform (WT) was recently employed.

WT is a relatively new and powerful tool in the field of signal processing, which overcomes problems that other techniques face with, especially in the processing of non-stationary signals. WT is not a self-adaptive signal decomposition method essentially [12]. Combet and Gelman have proposed optimal denoising, using Wiener filter based on the spectral kurtosis (SK) methodology, to enhance the small transients in gear vibration signals, in order to, detect local tooth faults such as pitting at early stage [13]. The problem of local fault detection in gears can be related to the more general problem of transient detection in a signal. In that purpose, a SK detection technique has been proposed [14]. The SK is a tool sensitive to non-stationary patterns in a signal and that can indicate at which frequencies those patterns occur. Furthermore, the SK can be used to design detection filters that adaptively extract the fault signal from the noisy background [13]. From the SK-based filtered residual signal, called the SK-residual, it is possible to define the local power as the smoothed squared envelope, which can be interpreted as the sum of the time-frequency energy distribution weighted by the values of the SK at each frequency, and so by the degree of non-stationary of the transients [13]. Wang [15] proposed to apply the resonance demodulation technique which was based on envelope analysis of the residual signal after band-pass filtering within an excited resonance. Multiwavelet denoising techniques suffer from such main drawbacks as the fixed basis functions independent of the input dynamic response signals and the universal threshold denoising [16]. This may lead to the loss of some critical but relatively weak information in the fault feature detection [16]. In order to overcome the above limitations for effective gear fault detection, a novel method incorporating the customized multiwavelet lifting schemes with sliding window denoising is proposed by the same authors. Proposed method outperforms various wavelet methods as well as SK [16].

Higher order cumulant (HOC) analysis, which is a new technology that has been developed rapidly in recent years, could be an important tool for the processing of non-Gaussian signals, nonlinear signals and the blind signal. Using [17] the HOC method, this paper analyzes signal features of a gear system with a single fault and complex fault. As the spectrum characteristics of the various faults are different they can be identified from them. The results show that the method has a notable advantage in detecting the secondary phase and higher order phase coupling characteristics of the vibration signal, and is an effective method of fault diagnosis for gear system. The effectiveness of the method under low running conditions is good; however it decreases in the high speed state, due to each order multi-frequency generated by the meshing frequency relating to the rotating speed that participate in the secondary and higher order phase coupling vibration. In the low speed state, the peaks are mainly concentrated in the low-frequency zone and the fault type is easily identified. As the speed increases the fault feature become less obvious and the distinguishing degree of various faults is reduced.

Based on the versatility and flexibility of Overcomplete rational dilation discrete wavelet transform (ORDWT), a fault feature extraction technique is proposed. The proposed technique [18] is applied in a range of engineering applications to extract fault features of various characteristics, including periodical impulses, AM/FM contents and transient vibration contents masked by overwhelming noise. In the diagnostic process, ORDWT is used as a pre-processing signal decomposition tool, and other auxiliary signal processing approaches are employed to post-process the reconstructed wavelet sub bands of the vibration signals according to specific analysis demands.

3. CONCLUSION

This paper provides a review of the literature, progress and changes over the years on feature extraction for fault detection of gears using vibration signal processing techniques. Time feature extraction methods try to offer more direct approach; however all of them do some sort of averaging on the signal, which might suffer loss of time information. This is a disadvantage when operating with signals that have very short duration or suddenly occurring component, like a signal generated from faulty gears. Time-frequency techniques are more advanced in localization of non-stationary gear fault feature from one point, but from another point they are more complicated to be implemented in practice. To date, various types of feature extraction methods have been proposed. However, the question of how to choose a suitable one among them to match the signal structure remains an open issue.

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METODE EKSTRAKCIJE VIBRACIONIH POKAZATELJA ZA DIJAGNOSTIKU ZUPČASTIH PAROVA – PREGLED

Ključni element kod praćenje stanja i dijagnostike oštećenja zupčanika jeste ekstrakcija obeležja oštećenja. Isto tako, u toku proteklih decenija izučavanje detekcije obeležja oštećenja rotirajućih mašina baziranih na analizi vibracija i dijagnostici privlačilo je stalnu pažnju. U većini slučajeva kako bi se utvrdilo stanje zupčastog prenosnika zahteva se proučavanje više od jednog obeležja ili kombinacija nekoliko tehnika. Ovaj rad pokušava da istraži i sumira nedavna istraživanja i razvoj metoda ekstrakcije obeležja u cilju dijagnostike oštećenja zupčanika, pruži referencu za istraživače u vezi s ovom temom i pomogne im u identifikaciji pravaca daljih istraživanja na ovu temu. Ukratko su

predstavljene metode ekstrakcije obeležja u cilju dijagnostike oštećenja zupčanika, ilustrovana je korisnost metoda i navedeni su problemi i odgovarajuća rešenja. Zatim, sažete su nedavne primene metoda ekstrakcije obeležja u cilju dijagnostike oštećenja zupčanika u pogledu zupčanika industrijskih zupčastih prenosnika. Na kraju, diskutovano je o problemima metoda ekstrakcije obeležja u cilju dijagnostike oštećenja zupčanika uz identifikaciju potencijalnih budućih istraživačkih pravaca. Očekuje se da će ovaj pregledni rad poslužiti kao uvodni sažetak metoda ekstrakcije obeležja u svrhu dijagnostike oštećenja zupčanika na bazi vibracija.

Ključne reči: *vibracije, zupčasti prenosnik, ekstrakcija vibracionih pokazatelja*