This is a post-peer-review, pre-copyedit version of an article published in Acoustics Australia. The final authenticated version is available online at:
https://doi.org/10.1007/s40857-021-00236-3

An overview of fault diagnosis of industrial machines operating under variable speeds

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Abstract: This paper provides an overview of the recent advances made in the field of fault diagnosis of industrial machines operating under variable speed conditions. First, the shortcomings of the traditional techniques in extracting reliable fault information are laid down, followed by a discussion on the different approaches adopted to overcome these issues. Next, these approaches are discussed by categorizing them as resampling based and resampling free methods. The principle and implementation procedures of these methods are discussed by summarizing the key literature in this area. Finally, the paper is concluded by highlighting the future challenges to address in this area.

1. Introduction

Fault diagnosis of rotating machines is crucial for their reliable operation and continuous availability [1]. Vibration analysis is one of the most effective fault diagnosis techniques, which relies on analysis of periodic events occurring in the system using vibration signals. For instance, a localized defect in a gear tooth causes periodic modulations in amplitude and phase of the measured vibration signal [2]. These modulations cause sidebands, which occur at the fault characteristic frequencies (FCFs), to appear around the gear-mesh frequency (GMF), and its harmonics [3]. The presence of the sidebands is used as an indicator to identify the gear faults in the frequency domain. The frequency-based spectral analysis approach is also applicable in case of other critical machine elements like bearings [4]. However, these methods are only valid under constant speed regimes. In practice, almost all industrial machines experience different levels of speed variations during operation. The presence of speed variation in a measured vibration signal makes it difficult for the classical fast Fourier transform (FFT) based methods to diagnose faults because the spectral lines of the constituent frequencies will widen leading to spectral smearing, as shown in Fig. 1.

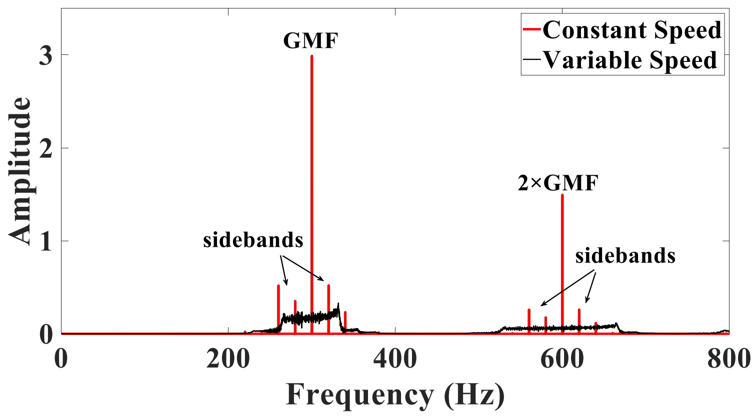

Figure 1: Spectrum of gear vibration signal under constant and variable speed conditions.

However, even though the periodicities in rotating machine vibration signals are lost in the time domain due to presence of speed variation, this periodic nature is preserved in the angular domain due to the signals being intrinsically angle-cyclostationary [5]. The concept of cyclostationarity has been successfully used to explain the signal characteristics of rotating machine components, like gears and bearings. By definition, an nth-order cyclostationary signal has periodic statistics of order n, i.e., a first-order cyclostationary (CS1) signal is characterized by a periodic mean, whereas a second-order cyclostationary (CS2) signal is characterized by a periodic auto-covariance function [6]. As the periodic patterns of machine signals are essentially locked to the angular positions of a machine shaft, the cyclostationary property remains valid in the angle domain under speed variations. Order tracking (OT) takes advantage of this phenomena by sampling signals at equi-angular intervals instead of time intervals [7, 8]. This angular domain resampling is generally realized using the instantaneous rotating speed information of the machines, which is measured using auxiliary sensors like tachometers. However, in industrial set-ups the reference speed signals are not always accessible due to non-availability of the extra sensors. To address these issues, tacho-less order tracking techniques [9], in which the rotating speed information is estimated from the measured vibration signal itself, have gained particular research attention. It is noteworthy that the angle-cyclostationarity of machine vibration signals is only intact under limited speed variation. However, when the speed variation is large, different machine components are observed to exhibit different properties requiring a more evolved analysis for proper fault diagnosis, which is discussed later in Section 2.

In addition to the frequency-based techniques, several fault diagnosis techniques also analyze vibration signals in the time [10] and the time-frequency [11] domains. The time domain techniques use statistical measures of the signal, like root mean square (RMS), skewness, or kurtosis, as fault indicators. However, these techniques are again valid only under constant speed as they are affected by the introduction of the additional signal modulation caused by the presence of speed variation [12]. Such modulations mask the defect-induced modulations present in the measured signal, causing the statistical measures to vary with the change in the speed. Thus, they cannot be used as reliable indicators for fault diagnosis under variable speed regimes. The time-frequency (TF) domain techniques, on the other hand, are efficient in handling signals measured under speed variations and they are also free from any propagation error observed in the resampling based techniques, due to polynomial interpolation [13, 14]. However, the TF-based techniques require a high resolution in both time and frequency necessitating high sampling rates for a large amount of time to generate a suitable time-frequency representation (TFR) of the measured signal [10]. A low resolution TFR generally fails to reveal the instantaneous fault characteristic frequencies (IFCF) and their higher harmonics, making it difficult to use them for reliable fault diagnosis.

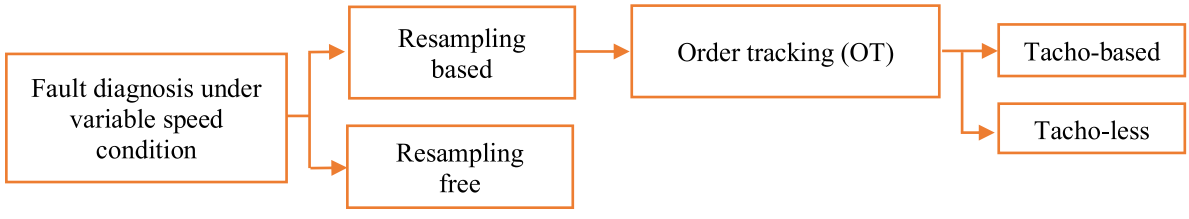

Figure 2: Overview of fault diagnosis techniques for variable speed conditions.

Thus, carrying out fault diagnosis under speed variation is challenging, and significant research efforts have investigated and developed new methods capable of providing reliable information about health of a machine. As discussed, most conventional fault diagnosis techniques under variable speed adopt resampling of the time domain signal to the angular domain to retain the signal periodicities. However, the accuracy of resampling is often dependent on the interpolation methods and estimation of an angular reference signal. As such, resampling free methods are gaining interest in machinery fault diagnosis due to their relatively simplified approach of extracting fault features directly from the measured signal. It is observed that rotating machine fault diagnosis under variable speed started with tachometer aided OT, where the measured signal is transformed to the angular domain using an auxiliary reference signal having information of the shaft phase. However, over time tacho-less OT methods gained popularity. In these methods, the signal resampling is achieved using either an extracted shaft harmonics based phase demodulation or an extracted instantaneous frequency of the shaft estimated using a time-frequency based ridge detection technique. Recently extensions of cyclostationary methods to analyze vibration signals under large speed variation using bi-variable 2D maps in order-frequency domain have gained attention along with the emergence of adaptive mode decomposition methods, time-frequency analysis, integral transform based order analysis and machine learning based methods. This paper reviews these different methods and highlights the recent trends in the field. Compared to some other recent review papers [9, 15] on this topic focusing mainly on the tacho-less OT methods and the corresponding speed estimation methods, this article provides a more comprehensive review, covering all the different fault diagnosis techniques under variable speed conditions, by broadly categorizing them into resampling based and resampling free methods. Figure 2 provides an overview of the classification approach used in this paper to present these existing techniques.

2. Resampling based methods

Order tracking**:** Order tracking (OT) is one of the widely used fault diagnosis techniques under speed variation [8, 13, 16]. The classical OT or hardware order tracking (HOT) uses analogue instruments to adjust the sampling rate proportional to the tachometer obtained shaft speed reference signal, to synchronously measure the vibration signal [7, 8]. However, under rapidly varying speed conditions, like run-ups and coast-downs, these analogue instruments fail to accurately track the shaft speed, leading to errors in sampling [7]. This drawback along with the advent of digital equipment led to the development of the resampling based computed order tracking (COT).

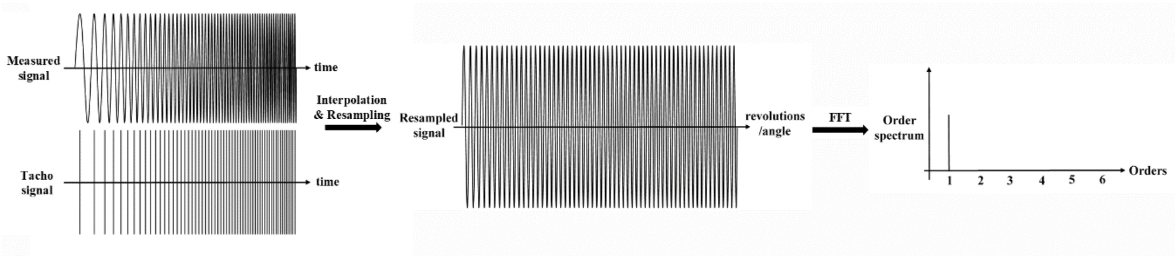

Figure 3: Steps involved in implementation of COT (reproduced from [13]).

In COT, the vibration signal and the phase reference pulse are first measured at constant time intervals, and then resampled digitally in the time-domain using the shaft phase information from the reference signal. As this resampling is performed in the time-domain, the phase to time transformation is achieved by applying a polynomial interpolation technique [13]. McFadden [17] discussed the use of different interpolation techniques to resample vibration signal. Figure 3 illustrates the implementation steps involved in COT. In 1997, Fyfe and Munck [8] demonstrated the use of cubic-spline based interpolation method to resample the vibration signal using a onceper-shaft revolution and a 3-pulse-per-shaft revolution tachometer signals for COT. Since then several tacho-based COT methods for fault diagnosis have been developed [18-22].

Tacho-less order tracking: The auxiliary hardware like a tachometer to generate the reference pulse required for COT is generally not available in an industrial setting, due to added costs and need for additional maintenance, and inconveniences arising from sensor malfunction [9]. This has led to much attention being focused on tacho-less OT methods, where the required reference signal can be estimated directly from the measured vibration signal. Bonnardot et al., [23] first demonstrated the idea of tacho-less OT, where the instantaneous phase information for signal resampling was obtained by phase demodulation of filtered out gear-mesh frequency or its higher harmonic signal from the vibration signal itself. Coats and Randall [24] further proposed a generalized method for tacho-less OT using a phase demodulation technique for speed variations up to ±30%. Hong et al., [25] proposed a new tacho-less OT method, as shown in Fig. 4, where the fast dynamic time warping (FDTW) algorithm was used to dynamically align a filtered shaft harmonic signal with a reference signal, constructed assuming a constant frequency. The measured vibration signal is then resampled based on the optimal warping path of the reference signal having a constant frequency. The warping process negates any phase estimation error due to speed variation. Other methods that use harmonic signal for OT include Bonnardot et al., [26], Urbanek et al., [27]. It is noteworthy that in the afore-described methods, the gear-mesh harmonic or the shaft harmonic required to perform the OT needs to be filtered out from the vibration signal, as shown in Fig. 4. This may limit their use to cases where the speed variation is relatively small (not more than ±33% if the first harmonic is used and even lesser variation if a higher harmonic is used) because of issues arising from overlapping of different frequency components [24]. Another class of tacho-less OT use adaptive mode decomposition methods [28-31]. However, these techniques also have limited applicability under large speed variations. One of the ways to extend these tacho-less methods for larger speed variations is by adopting TFR based instantaneous frequency (IF) estimation via ridge detection, which provides the phase information of the reference shaft for the signal resampling step of OT. Zhao et al., [32] estimated the instantaneous frequency of the required harmonic using short-time Fourier transform (STFT) and refined by Chirplet transform (CT), followed by using the time-varying Vold-Kalman filter (VKF) to extract the harmonic signal. Finally, the measured vibration signal was resampled using the instantaneous phase of the reference shaft, estimated from the filtered harmonic. There are several methods that adopt TFR based IF estimation for tacho-less OT [33-38].

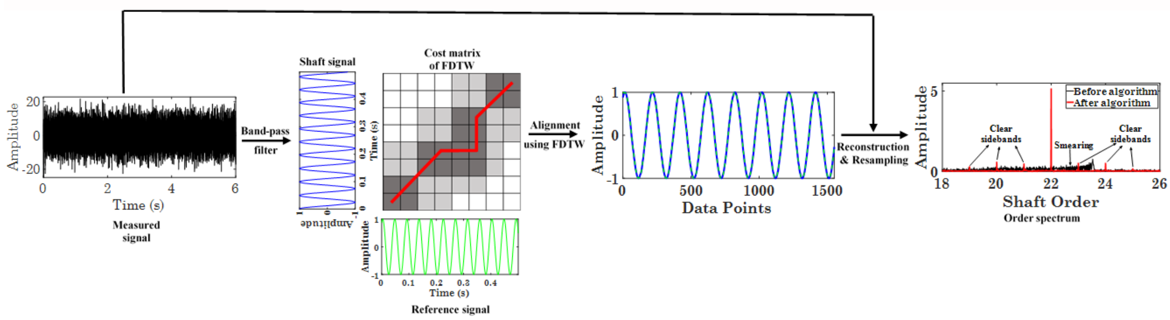

Figure 4: Steps involved in FDTW-based tacho-less OT proposed by Hong et al., [25].

However, under large speed variations OT based spectral analysis alone may not be sufficient and it may lead to misrepresentation of the signal characteristics. This may be attributed to the fact that a machine vibration signal consists of a series of periodic impact responses whose occurrence is synchronous with a shaft angle. However, the responses themselves have constant time interval characteristics that are related to the system dynamics (structural resonances that are fixed in Hz), which become variable when transformed in the angular domain [39, 40]. Therefore, under speed variation when the time spacing between the periodic impacts become inconsistent, applying angular resampling based OT converts the periodic impacts to be constant in the angular domain, wherein the structural resonance appear to be variable. Figure 5(a) shows a spectrogram of a typical faulty bearing vibration signal, where the resonance region is indicated through the horizontal frequency band. Figure 5(b) shows the spectrogram of the signal after performing angular resampling and the resonance frequency is now observed to be variable. Other dominant frequencies in Fig. 5(a) are the variable fault characteristic frequency (FCF) and its harmonics, which transform into constant horizontal lines after the application of angular resampling, as observed in Fig. 5(b). It is the presence of this duality, as demonstrated in Fig. 5, in the angle and the time domains that makes the angle-cyclostationarity based OT analysis ineffective. These machine vibration signals under large speed variations are coined as cyclo-non-stationary (CNS), and it is realized that such signals require a joint treatment in the angle/time (or order/frequency) domains to fully capture their characteristics, rather than analyzing in the order domain alone [41, 42].

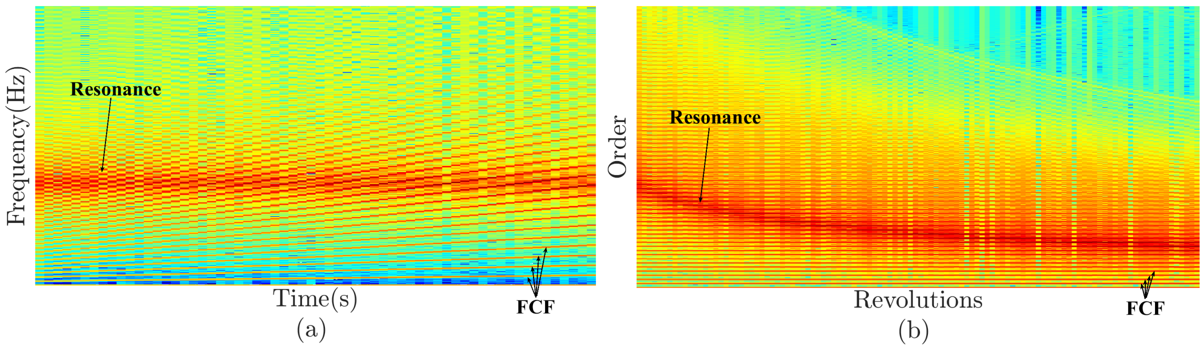

Figure 5: Spectrogram of a faulty bearing vibration signal under variable speed operation (a) before angular resampling, and (b) after angular resampling.

Recently, the angular resampling based technique was extended to time-frequency domain in order to obtain order-frequency domain or order-order domain representations [11, 43-46]. D'Elia et al. [47] first proposed an order–frequency distribution to concurrently describe the angular periodicities and the time dynamics of the signal using the order variable and the frequency variable in a bi-variable 2D map. Mauricio et al. [11] overcame the spectral smearing in cyclostationary tool based bi-variable maps in frequency-frequency domain by transforming the vibration signal to the angle domain before the calculation of the cyclostationary tools in order to obtain the order-order representation of the vibration signal. Resampling of the time-frequency domain to the angular domain, in order to obtain the angular-frequency domain map leading to the order-frequency cyclic modulation spectrum has been proposed as a tool to detect hidden modulations under varying speed conditions [39, 48]. These concepts are found to be more applicable for bearing diagnostics. For gears, the presence of large speed variation is likely to force the gear-mesh frequency to pass through structural resonances, which lead to additional amplitude modulations of the system response that can be misinterpreted if the vibration analysis is performed only in the order domain. This is because under such situations, the resampling based OT technique is only able to compensate for frequency variation effects, by converting the frequency axis to be in terms of harmonic orders of a reference shaft frequency, but has no influence on the additional amplitude modulation induced due to the presence of large speed variation, as shown in Fig. 6. Gear diagnostics under such regimes can be also be improved by processing in the order-frequency domain [47].

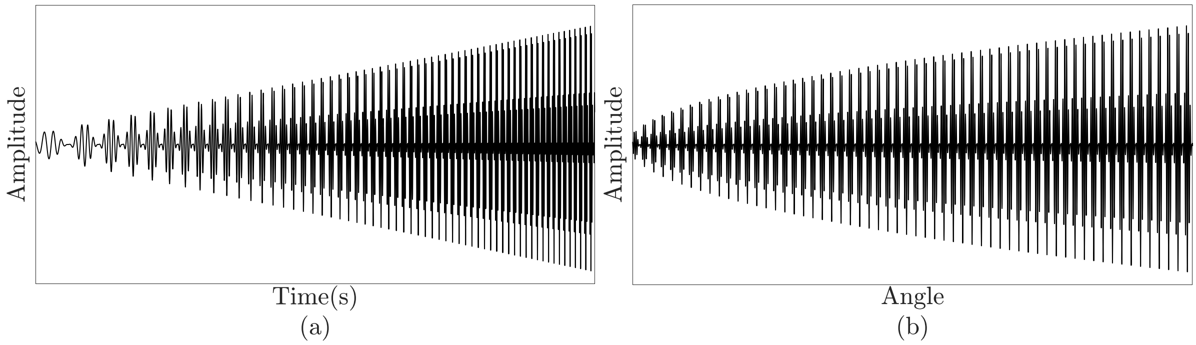

Figure 6: Gear vibration signal with amplitude modulation under large speed variation (a) before angular resampling, and (b) after angular resampling.

Apart from resampling in the frequency and the time-frequency domains, there are other resampling based fault diagnosis methods in the time domain [10] as well. Hong et al., [10] proposed a time domain based fault diagnosis method combining fast dynamic time warping (FDTW) and correlated kurtosis (CK). This method calculated a residue signal after warping a band-pass filtered gear-mesh harmonic signal over a reference signal, which was constructed assuming a defect-free, constant-speed operation. The CK and root mean square (RMS) values of the residue signal were used to identify the location and severity of faults in the case of a planetary gearbox. Researchers have proposed several other time domain methods based on signal resampling [12, 49-51].

3. Resampling free methods

This section discusses the fault diagnosis techniques under speed variations that do not resample the vibration signal from time to angle domain. The resampling based methods are affected by various factors such as the accuracy of the obtained shaft speed information and the method of interpolation used for resampling [52]. Moreover, the OT process is also affected by the sensor signal transmission path phase [52]. The resampling free methods provide an alternative way to carry out fault diagnosis under variable speed conditions, which are not dependent on resampling accuracy. Most of these methods are generally based on the time-frequency analysis. Short-time Fourier transform (STFT), wavelet transform (WT), Wigner-Ville distribution (WVD), and Hilbert-Huang transform (HHT) are used to obtain the TFR of the measured vibration signal [14, 52], where the instantaneous fault characteristic frequency (IFCF) and its higher harmonics can be visualized as ridges as shown in Fig. 7.

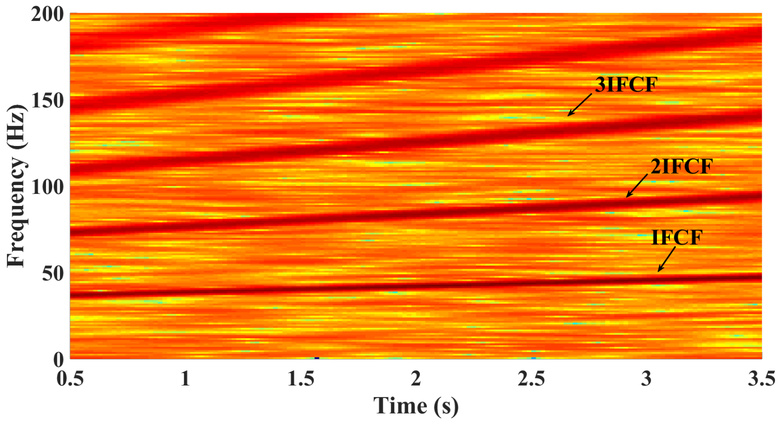

Figure 7: Enhanced TFR with visible IFCF and its harmonics, for fault diagnosis [52].

These visualizations aid in fault diagnosis without any signal resampling. Meltzer and Dien [53] applied continuous wavelet transforms, Williams and Zalubas [54] applied Wigner-Ville distribution (WVD) for fault diagnosis in gearboxes. To improve the readability of the TFR, Li and Liang [55] and Feng et al. [56] used generalized synchrosqueeze transform (GST) that can both carry out signal transforms and time-frequency enhancement in order to identify the fault induced instantaneous frequencies in the TFR. Hilbert transform (HT) based methods have also been studied extensively for their fine time-frequency resolution [57]. However, they require the analyses signal to be mono-component in nature [58]. Empirical mode decomposition (EMD) [59] and its variants [29, 60] have been used to adaptively extract constituent mono-components of a vibration signal by means of numerical approximation. However, they suffer from issues like mode mixing due to spectral overlaps between components, which limits their applicability since the constituent components are bound to have overlapping of frequencies under large speed variations. Another important class of resampling free methods is based on the Vold-Kalman filter (VKF). VKF is used for separating a harmonic component from a multi-component vibration signal under speed variations [61, 62]. VKF extracts this harmonic component by acting as a time-varying filter, where the center frequency varies according to the initial estimate of the instantaneous frequency, thus fulfilling the mono-component requirement and enabling construction of easily interpretable time-frequency representations based on Hilbert transform for complex time-varying IFCF identification. Methods based on generalized demodulation (GD) are also studied for fault diagnosis, where the time-varying instantaneous frequencies are converted into constant frequency lines in the time-frequency plane by iteratively applying GD [14, 57, 63-66]. These methods require a peak search algorithm or ridge extraction for estimating the initial time-frequency curves [33, 52, 67-69]. Huang et al., [68] proposed an algorithm for multiple time-frequency curve extraction based on iteratively using a fast optimization approach, which optimally extracts a string of peaks along the time span. However, it has been observed that the TF curve extraction methods have limitations in presence of random noise and multi-source interference. Moreover, these time-frequency domain based methods also suffer in terms of heavy computational burden, as they require high resolution TFRs for accurate estimation of the instantaneous frequency curves. Other resampling free methods for fault diagnosis under speed variations include Borghesani et al., [16] and Sharma et al., [12, 70].

4. Discussion and Future trends

This section summarizes the different fault diagnosis methods under variable speed conditions along with a discussion on the challenges that still need to be addressed in order to make these methods more efficient and reliable in practice. It is observed that for machinery fault diagnosis under variable speed, angular resampling of the measured vibration signal according to the variable speed profile is capable of transforming the time-varying FCFs into constant orders of a reference shaft speed. This transformation forms the basis of the order tracking analysis, where the time-varying FCFs are detected by recognizing the order peaks in a spectral representation. However, the signal resampling process is itself limited by factors such as the accuracy of the obtained shaft speed. The angular resampling based order analysis also depends on the assumption that all frequency constituents of measured vibration signals are orders of the shaft speed. However, it is observed that under large speed variations such assumptions may not always hold true, as resonances, which are independent of the shaft speed, are also present. Resonance characteristics, which are necessarily fixed in frequency, are distorted by angular resampling. As a result, these components cause smearing in the obtained order spectrum, masking relatively weak fault features and leading to false detection of pseudo orders. Under these conditions fault diagnosis is improved by adopting a joint analysis of the measured signal in both the angle and the frequency domains by extending angular resampling to generate different order-frequency and order-order maps under the cyclo-non-stationary analysis framework. It is, however, noteworthy to mention that the resampling of the measured vibration signal is dependent on precise estimation and extraction of shaft speed information.

Besides resampling based methods, researchers have also concurrently emphasized on developing fault diagnosis methods that are resampling free such that the measured vibration signal can be directly analyses to reveal the fault features. Time-frequency analysis has been found to be effective in this category as the varying frequencies appear as “ridges” in a well-processed, high resolution TFR and as such the relevant fault characteristics of the measured vibration signal can be represented in the joint time-frequency domain. However, due to the Heisenberg’s uncertainty principle, high resolution of the time and the frequency domains are often not achieved simultaneously, which can lead to a weak TFR that fails to properly reveal the fault features. Efforts are directed towards improving the readability of the TFRs and develop techniques to extract accurate instantaneous frequency information via effective ridge detection.

Therefore, based on the review of the various fault diagnosis methods under variable speed operation, some of the trends for future consideration are summarized as follow,

4.1. Accurate estimation of instantaneous frequency

Techniques like the tacho-less order tracking methods and time-frequency analysis are generally dependent on the accuracy of TFR based instantaneous frequency (IF) estimation methods. More advanced and accurate IF estimation methods based on TFR, especially in low signal-to-noise ratio scenarios and where there is presence of interference in the measured signal, could be introduced [33, 67, 68]. These methods can be then applied for order tracking of measured signal to improve the diagnosis accuracy and efficiency. Moreover, they can also be used in conjunction with computationally less taxing high-resolution TFR methods for resampling free fault diagnosis.

4.2. Adaptive selection of parameters for automatic fault diagnosis

One of the drawbacks observed in the current fault diagnosis methods is their dependency on selection of adjustable parameters that rely on expert knowledge. The use of a band-pass filter or Vold-Kalman filter to extract shaft frequency harmonic mono-components from the measured signal depends on the selection of adjustable filter parameters that can have significant impact on the performance of the fault diagnosis methods. The same drawback is also present in many time-frequency analysis methods like the short-time Fourier transform, wavelet transform, where the window or wavelet length choice plays a role in accurate capture of the signal characteristics. In the future, methods capable of adaptively estimating and tuning the adjustable parameters could be developed for automatic fault diagnosis.

4.3. Use of machine learning techniques

In the age of Industry 4.0, there is a need for fault diagnosis methods to be intelligent where the algorithms automatically recognize the health status of any machine without the need of any expert knowledge or intervention. Machine learning (ML) techniques [71] have been found to be effective under such requirements as they are able to automatically extract features from measured signals that can be utilized for fault diagnosis. However, there is considerable scope for extension of these techniques for fault diagnosis under speed variation [72-83]. The current ML based fault diagnosis techniques, most handling constant speed cases, are incapable of extracting proper fault features for training the ML algorithms due to the presence of variability of the measured machine datasets caused by varying running conditions. In the future, methods capable of extracting reliable fault features from low signal-to-noise ratio measured signals could be developed to utilize the feature learning and classification capabilities of the state-of-the-art ML algorithms for intelligent fault diagnosis under time-varying speed conditions.

Table 1. Overview of fault diagnosis methods under variable speed conditions.

Machine component	Method	References	Key techniques
Gear	Resampling based	[8, 18]	Tacho-based OT
		[24-27]	Tacho-less OT, phase demodulation
		[28, 30, 31]	Tacho-less OT, phase demodulation, adaptive mode decomposition
		[32, 35]	Tacho-less OT, TFR based ridge detection, Vold-Kalman filter
		[47]	Cyclo-non-stationary analysis
		[10, 49-51]	Time domain features
		[22, 73, 78-80]	Machine learning, OT, TFR
	Resampling free	[53-57, 60-62, 64]	TFR, integral transforms, Vold-Kalman filter
		[63]	Integral transform based order analysis
		[58, 70]	Adaptive mode decomposition
		[12]	Time domain features
		[76, 82, 83]	Machine learning, signal decomposition
Bearing		[19-21]	Tacho-based OT

	Resampling based	[23, 24, 27]	Tacho-less OT, phase demodulation
		[33, 34, 36-38]	Tacho-less OT, TFR based ridge detection, adaptive mode decomposition, integral transforms
		[11, 39-47]	Cyclo-non-stationary analysis
		[74, 77-79, 81]	Machine learning, OT, TFR, adaptive mode decomposition
	Resampling free	[14, 52, 55-57, 60, 67-69]	TFR, integral transforms, adaptive mode decomposition
		[16, 65, 66]	Integral transform based order analysis
		[72, 75]	Machine learning

5. Conclusion

This paper presents an overview of the existing fault diagnosis methods under speed variation by categorizing them into resampling based and resampling free methods depending on whether the time domain vibration signal needs to be transformed to equi-angular intervals using the shaft rotational speed. The different references reviewed in this paper are classified based on their core methods and key techniques in Table 1. It has been observed that angular resampling based order analysis is one of the widely used techniques for fault diagnosis under speed variation as they utilize the angle-cyclostationary feature of rotating machine vibration signals to reveal the fault induced periodicities. Several time domain and time-frequency domain fault diagnosis methods also utilize resampled angular-domain vibration signals for fault diagnosis. The efficiency of the resampling based methods are generally found to be dependent on the availability of an accurate reference shaft speed signal and the phase-time transformation step achieved by applying polynomial interpolation technique. The resampling free fault diagnosis methods, on the other hand, do not require any angular domain resampling as the measured vibration signal is directly utilized to reveal the fault induced periodicities. However, the resampling free methods, especially the TFR based methods are computationally taxing and suffer from low-resolution issues, which affect their diagnosis accuracy. Therefore, fault diagnosis under speed variation still has challenges that provide opportunities for future research, especially in the area of estimating accurate instantaneous frequency from measured vibration signal using TFR, such that effective and accurate tacho-less resampled based methods as well as resample free methods that work under large speed variations and low signal-to-noise ratio scenarios can be developed. Moreover, adaptive parameter tuning methods and the use of machine learning algorithms to develop intelligent automatic fault diagnosis methods also has a potential for future research in this area.

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