Chapter 2

Literature Review

'*I have seen farther by standing on the shoulders of giants.*'

-Isaac Newton

The knowledge-base in the area of bearing fault diagnosis is ever increasing due to gigantic amount of literature. The accessibility and dissemination of knowledge due to digitisation are major factors taking the research forward in this area.

Highlights:

- Bearing fault diagnosis has three important steps - measurement, signal processing and decision making.
- Vibration signals are most commonly used for diagnosis, followed by acoustic emission, sound and current signature.
- Out of several processing techniques, wavelet and empirical mode decomposition based methods are most commonly found in the literature. The performance of wavelet based methods mainly depends on the selection of mother wavelet.
- Fractional domain processing is introduced and has a potential of enhancing fault features in fractional domain.

Bearing fault diagnosis is a classical research problem, which has been of prime industrial and academic interest. The gigantic amount of literature in this field is ever increasing in size and this trend can be seen in Fig. 2.1. Historically, the field of bearing fault diagnosis has evolved due to breakthroughs in various areas of science and technology. Earlier fault diagnosis equipments were too bulky, with simple algorithms and with less processing power. In 1970s, the real-time analysers weighed around 50 lbs [30]. However, introduction of fast Fourier transform (FFT) and development of small computers revolutionised the way machine faults were diagnosed.

Since the earliest research on machine fault diagnosis, vibration and sound monitoring are commonly practised and require human expertise. The time domain analysis techniques reveals very little information about the fault. Even the frequency domain representation of bearing signal suppresses the fault signature because of complex modulation that occurs due to structural elements of the machine. During the surface-to-surface impact between the faulty raceway and rolling element, a high frequency resonance is generated, which is dominantly observed in the frequency spectrum. Whereas, the actual diagnostic information lies in the fault characteristic frequencies that appear in low range of the spectrum. To reveal this crucial signature in the frequency domain, the signal needs to be demodulated. Therefore, envelope spectrum is almost an irreplaceable part of bearing fault diagnosis algorithms.

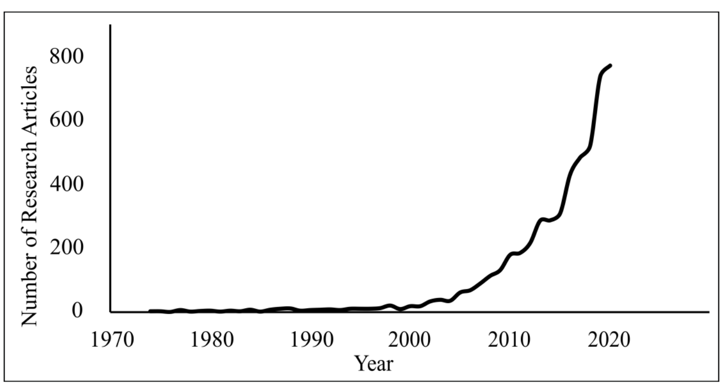

Figure 2.1: Bearing fault diagnosis research trend (From *Scopus* database)

The development of various signal processing tools has been instrumental in the progress made in bearing fault diagnosis. As shown in Fig. 2.2 and 2.3, signal processing is mainly used in bearing fault diagnosis to address two key issues - how to represent the bearing signal properly and how to demodulate it.

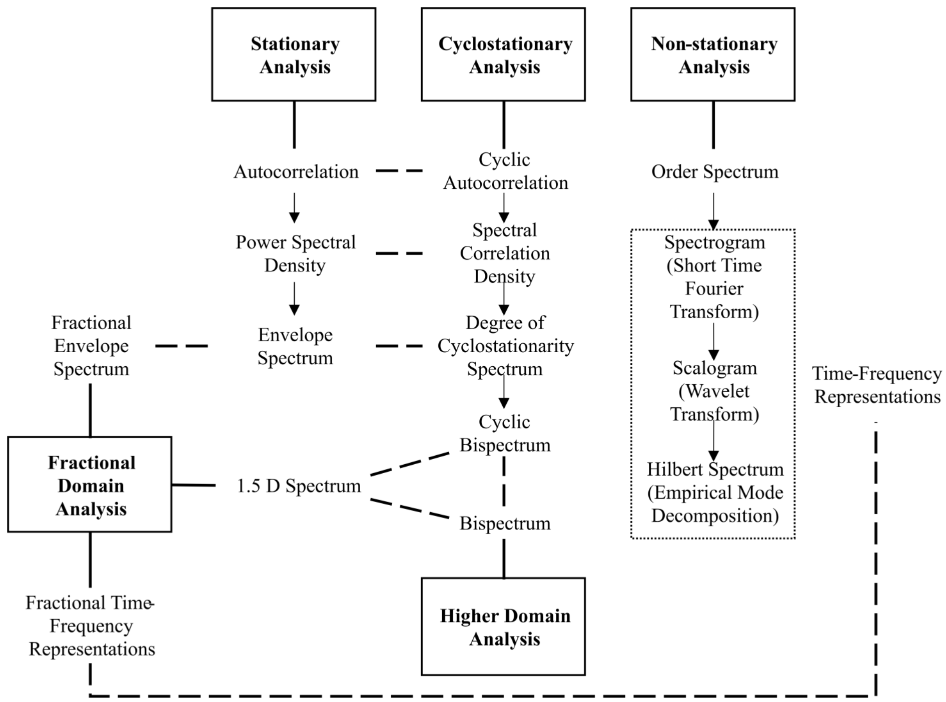

Figure 2.2: Evolution of different signal processing techniques in bearing fault diagnosis for appropriate signal representation. (Dashed lines show that the concepts are closely related.)

Bearing fault signals are cyclostationary in nature under constant speed and non-stationary under variable speed. Thus the evolution of cyclic domain and time-frequency domain representations is very important. The cyclostationary methods mainly use spectral correlation density for representing the fault characteristic frequency (FCF) and resonant frequency in the same plot. Though such representation is practically difficult to interpret, it provides a framework and theoretical basis to highlight the importance of squared envelope spectrum. Non-stationarity analysis, on the other hand, has evolved from spectrograms (short time Fourier transform) to Hilbert-Huang spectrum (empirical

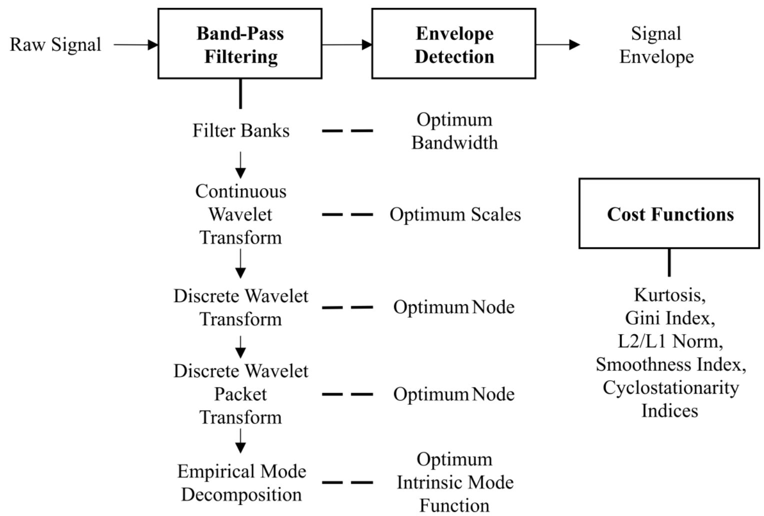

Figure 2.3: Evolution of different signal processing techniques in bearing fault diagnosis for signal demodulation.

mode decomposition). Wavelet based scalograms are also widely used for representing the bearing signal in time-frequency domain. Another approach includes the order tracking analysis, in which, bearing signal is first converted to a resampled signal based on the instantaneous rotational speed and converted to the angle domain. Then its envelope spectrum is calculated to analyse the faults at fault characteristic orders (FCO), which are multiples of the rotational speed.

Although, all these methods are reported in the literature, envelope spectrum and envelope order spectrum are predominant because of their simplicity. But, the signal transformations for non-stationary analysis are very efficient to solve the other issue - demodulating the bearing signal. As shown in Fig. 2.3, signal demodulation is carried out in two steps - band pass filtering and envelope detection. Envelope detection is most commonly carried out using Hilbert transform, but, band pass filtering is the most elusive problem of bearing fault diagnosis. Several research articles are dedicated to this in a quest of finding the optimum resonance band that contains the fault information. Earlier research uses filter banks with kurtosis maximisation to select the optimum band. This technique, known as the kurtogram, is a common practice, but it later evolved into the wavelet based and empirical mode decomposition based algorithms. Following subsections discuss these issues with the help of existing literature in the field.

2.1 Wavelet Decomposition Methods

The kurtogram method was initially introduced in [31, 32] as a kurtosis maximised optimum band pass filtering, followed by envelope spectrum analysis. This was later adapted using wavelets as a filter bank, but several articles are often reported as a modification of the kurtogram, based on the simple band pass filtering [33–38] or short-time Fourier transform (STFT) [39]. But, based on the selection of appropriate basis function, wavelet analysis gives prominent fault features compared to simple band pass filter or STFT by removing intra-band and in-band noise. Earlier work on application of continuous wavelet transform (CWT) established its superiority over the envelope spectrum [40]. The faults are diagnosed from the scalogram based on the theoretical value of fault characteristic frequency (FCF). A similar attempt is made in [41], using impulse response wavelet, but the faults are diagnosed from Scale-Wavelet Power Spectrum.

Use of narrow-band envelopes after wavelet decomposition is suggested in [42], and the performance of matching pursuit based Gabor time-frequency atoms is better than the conventional CWT. Although this work suggests the idea of narrow-band envelopes, selection of scales representing the resonance band is not methodical. This issue is well-addressed in [43–48]. These works use different mother wavelets and different optimisation criteria, but the purpose is to select appropriate scales to represent the resonance band. [49] puts forth the idea of calculating envelope spectrums for multiple scale values and then creating a waterfall diagram, called multiple-scale enveloping spectrogram (MuSEnS), for diagnosis. CWT has redundant information and is computationally expensive. Therefore, to compete with the fast kurtogram technique and to incorporate the advantages of wavelet analysis, the use of discrete wavelet transform (DWT) is reported in [50–56]. Application of wavelet packet transform is suggested in [40, 57–59], as it decomposes both the approximations and details, which provides better choice of the resonance band selection.

A detailed review of literature, focusing on wavelets for bearing fault diagnosis, is summarised in Table 2.1. Few important observations from this review are -

1. Continuous wavelet transform (CWT) is computationally expensive, has redundant information and requires an optimisation algorithm to find the optimum scale containing prominent fault information. On the other hand, discrete wavelet transform (DWT) or discrete wavelet packet transform (WPT) are computationally less complex and finding the optimum node does not require an optimisation algorithm because of finite number of nodes.
2. Lifting scheme is often reported in the literature to construct suitable wavelet for bearing fault diagnosis.
3. Several base wavelets are found in the literature. Out of these Morlet and impulse response wavelet is widely accepted as the most suitable ones for bearing fault diagnosis.
4. Finding the optimum node is still an elusive problem, as the resonance frequency band is not exactly known. The level of decomposition is often chosen greater than or equal to 5. Whereas, kurtosis is a standard selection criteria for finding the optimum node.
5. Though kurtosis is the most widely used criteria for selection of optimal wavelet band, there are several other which are reported in the literature, like smoothness index, Gini index, L_2/L_1 norm.
6. For denoising, energy or entropy based thresholding is often recommended.

Table 2.1: Review of wavelet analysis (CWT - Continuous Wavelet Transform, DWT - Discrete Wavelet Transform, WPT - Wavelet Packet Transform, DB - Daubechies Wavelet Family, L* - Maximum Level of Decomposition)

Title	**Measurement**	**Decomposition**	**Spectral Analysis**	**Features**	**Classification**
Wavelet analysis and envelope detection for rolling element bearing fault diagnosis—their effectiveness and flexibilities (Tse *et al.* 2001) [60]	Vibration	CWT (Gaussian)	Envelope Spectrum	Fault Time Period	Visual
Bearing failure detection using matching pursuit (Liu *et al.* 2002) [42]	Vibration	CWT, Matching Pursuit (Gabor Time-Freauency Atoms)	Narrow Band Envelopes	Fault Time Period	Visual
Application of discrete wavelet transform for detection of ball bearing race faults (Prabhakar *et al.* 2002) [50]	Vibration	DWT (DB4, L4)	NA	Fault Time Period	Visual
Singularity analysis using continuous wavelet transform for bearing fault diagnosis (Sun and Tang 2002) [43]	Vibration	CWT (Gaussian, Lipschitz exponent for optimum band selection)	NA	Fault Time Period	Visual
Multi-fault diagnosis of rolling bearing elements using wavelet analysis and hidden Markov model based fault recognition (Purushotham *et al.* 2005) [51]	Vibration	DWT (DB2, L4)	NA	Mel Frequency Complex Cepstrum Coefficients	HMM
Fault diagnosis of rolling element bearings using basis pursuit (Yang *et al.* 2005) [57]	Vibration	WPT (Symlet8)	NA	Fault Time Period	Visual
Application of an impulse response wavelet to fault diagnosis of rolling bearings (Junsheng *et al.* 2007) [41]	Vibration	CWT (Impulse Response Wavelet)	Scale-Wavelet Power Spectrum	NA	Visual
A joint resonance frequency estimation and in-band noise reduction method for enhancing the detectability of bearing fault signals (Bozchalooi and Liang 2008) [44]	Vibration	CWT (Gabor Wavelet-Scale and Shape factor Selection)	NA	Kurtosis, Smoothness Index	Visual
An extended wavelet spectrum for bearing fault diagnostics (Liu *et al.* 2008) [52]	Vibration	DWT (Morlet,L7)	Autocorrelation Spectrum	Fault Characteristic Frequencies	Visual
Customized wavelet denoising using intra- and inter-scale dependency for bearing fault detection (Zhen *et al.* 2008) [53]	Vibration	DWT (Custom-Kurtosis Maximised, L4)	Envelope Spectrum	Fault Characteristic Frequencies	Visual
Morphological undecimated wavelet decomposition for fault diagnostics of rolling element bearings (Hao and Chu 2009) [61]	Vibration	Mathematical Morphology Based Wavelet	FFT Spectrum	Fault Characteristic Frequencies	Visual

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Table 2.1 – continued from previous page

Title	Measurement	Decomposition	Spectral Analysis	Features	Classification
Bearing fault detection based on optimal wavelet filter and sparse code shrinkage (He *et al.* 2009) [54]	Vibration	Intra-Band: Morlet Wavelet (Kurtosis Optimised), In-Band: Sparse Code Shrinkage, Optimization: Differential Evolution	Envelope Spectrum	Fault Characteristic Frequencies	Visual
Fault severity assessment for rolling element bearings using the Lempel-Ziv complexity and continuous wavelet transform (Hong and Liang 2009) [45]	Vibration	CWT (Morlet, Kurtosis and Energy Maximized)	NA	Lempel-Ziv complexity	Visual
Multi-scale enveloping spectrogram for vibration analysis in bearing defect diagnosis (Yan and Gao 2009) [49]	Vibration	CWT (Morlet)	Scalogram	Fault Characteristic Frequencies	Visual
Energy-based feature extraction for defect diagnosis in rotary machines (Yan and Gao 2009) [46]	Vibration	CWT (Morlet), Selection by Energy-Bandwidth Ratio	Envelope Spectrum	Fault Characteristic Frequencies	Visual
Rolling element bearing fault diagnosis based on the combination of genetic algorithms and fast kurtogram (Zhang and Randall 2009) [33]	Vibration	Fast Kurtogram, Genetic Algorithm (Kurtosis Optimisation)	Envelope Spectrum	Fault Characteristic Frequencies	Visual
Detection of signal transients based on wavelet and statistics for machine fault diagnosis (Zhu *et al.* 2009) [47]	Vibration	CWT (Morlet), K-S Test	NA	Fault Time Period	Visual
Rolling element bearing fault detection based on optimal antisymmetric real Laplace wavelet (Feng *et al.* 2011) [48]	Vibration	CWT (Laplace Wavelet - Kurtosis Maximised)	Envelope Spectrum	Fault Characteristic Frequencies	Visual
Rolling element bearing fault diagnosis using wavelet transform (Kankar *et al.* 2011) [55]	Vibration	DWT (Complex Morlet, L7), Shannon Entropy Minimised	NA	Kurtosis, Skewness, Standard Deviation	Support vector machines, self organizing maps
Transient modeling and parameter identification based on wavelet and correlation filtering for rotating machine fault diagnosis (Wang *et al.* 2011) [62]	Vibration	Periodic Multi-Transient Wavelet Model	NA	Fault Time Period	Visual
Multiwavelet denoising with improved neighboring coefficients for application on rolling bearing fault diagnosis (Wang *et al.* 2011) [63]	Vibration	Multiwavelet (Geronimo, Hardin, Massopust), NeighCoeff Optimised	Envelope Spectrum	Fault Characteristic Frequencies	Visual
Identification of multiple transient faults based on the adaptive spectral kurtosis method (Wang and Liang 2012) [34]	Vibration	Adaptive Filtering, Spectral Kurtosis	Envelope Spectrum	Fault Characteristic Frequencies	Visual

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Table 2.1 – continued from previous page

Title	Measurement	Decomposition	Spectral Analysis	Features	Classification
A kurtosis-guided adaptive demodulation technique for bearing fault detection based on tunable-Q wavelet transform (Luo *et al.* 2013) [64]	Vibration	Tunable Q Wavelet, Kurtosis Maximisation	Envelope Spectrum	Fault Characteristic Frequencies	Visual
Early classification of bearing faults using morphological operators and fuzzy inference (Raj and Murali 2013) [65]	Vibration	Mathematical Morphology (Top Hat, Beucher Gradient, Kurtosis based selection)	FFT Spectrum	Fault Characteristic Frequencies	Fuzzy Inference System
The design of a new sparsogram for fast bearing fault diagnosis: Part 1 of the two related manuscripts that have a joint title as "two automatic vibration-based fault diagnostic methods using the novel sparsity measurement - Parts 1 and 2" (Tse and Wang 2013) [58]	Vibration	WPT (DB10, L4, L2/L1 Norm Optimised)	Envelope Power Spectrum	Fault Characteristic Frequencies	Visual
The automatic selection of an optimal wavelet filter and its enhancement by the new sparsogram for bearing fault detection: Part 2 of the two related manuscripts that have a joint title as "two automatic vibration-based fault diagnostic methods using the novel sparsity measurement - Parts 1 and 2" (Tse and Wang 2013) [59]	Vibration	WPT (Morlet, L4, L2/L1 Norm Optimised, Genetic Algorithm)	Envelope Power Spectrum	Fault Characteristic Frequencies	Visual
A new statistical modeling and detection method for rolling element bearing faults based on alpha-stable distribution (Yu *et al.* 2013) [35]	Vibration	Band-pass Filter Bank (Alpha-stable fitting, Alpha Minimised)	Envelope Spectrum	Fault Characteristic Frequencies	Visual
Automatic fault feature extraction of mechanical anomaly on induction motor bearing using ensemble super-wavelet transform (He *et al.* 2015) [66]	Vibration	Tunable Q Wavelet (Subband energy ratio stoppage, Fault Characteristic Frequencies feature Maximisation)	Envelope Spectrum	Fault Characteristic Frequencies	Visual
Wavelet Packet Envelope Manifold for Fault Diagnosis of Rolling Element Bearings (Wang and He 2016) [67]	Sound	Wavelet Packet Transform	Envelope using Manifol Learning	FCF	Visual
The infogram Entropic evidence of the signature of repetitive transients (Antoni 2016) [39]	Vibration	STFT (Spectral Negentropy Optimised)	Squared Envelope Spectrum	Fault Characteristic Frequencies	Visual

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Table 2.1 – continued from previous page

Title	Measurement	Decomposition	Spectral Analysis	Features	Classification
Multi-frequency weak signal detection based on wavelet transform and parameter compensation band-pass multi-stable stochastic resonance (Han *et al.* 2016) [56]	Vibration	DWT (DB, L6, Multi-Stable Stochastic Resonance)	Frequency Spectrum	Fault Characteristic Frequencies	Visual
Optimised Spectral Kurtosis for bearing diagnostics under electromagnetic interference (Smith *et al.* 2016) [36]	Vibration	Kurtosis Maximised Band-pass Filtering	Squared Envelope Spectrum	Fault Characteristic Frequencies	Visual
Kurtosis based weighted sparse model with convex optimization technique for bearing fault diagnosis (Zhang *et al.* 2016) [68]	Vibration	Tunable Q Wavelets (Kurtosis-weighted Sparsity Model, L4)	Envelope Spectrum	Fault Characteristic Frequencies	Visual
Improvement of kurtosis-guided-grams via Gini index for bearing fault feature identification (Miao *et al.* 2017) [37]	Vibration	Filter Bank (Gini Index Optimised)	Envelope Spectrum	Fault Characteristic Frequencies	Visual
A new family of model-based impulsive wavelets and their sparse representation for rolling bearing fault diagnosis (Qin 2018) [69]	Vibration	Impulse Wavelet (Sparsity Optimised)	Envelope Spectrum	Fault Characteristic Frequencies	Visual
Nonconvex Sparse Regularization and Convex Optimization for Bearing Fault Diagnosis (Wang *et al.* 2018) [70]	Vibration	tunable Q-factor wavelet transform (L1 Norm generalized minimax-concave (GMC) penalty, L4)	Squared Envelope Spectrum	Fault Characteristic Frequencies	Visual
Automated bearing fault diagnosis scheme using 2D representation of wavelet packet transform and deep convolutional neural network (Islam and Kim 2019) [71]	Acoustic Emission	Wavelet Packet Transform (DB, L7)	DDRgram (Degree of Defectiveness)	NA	Convolutional Neural Network
Adaptive Kurtogram and its applications in rolling bearing fault diagnosis (Xu *et al.* 2019) [72]	Vibration	Order Statistics Filter based Bandwidth Segmentation, Empirical Wavelet Decomposition (Meyer)	Envelope Spectrum	Fault Characteristic Frequencies	Visual
An Adaptive Spectral Kurtosis Method and its Application to Fault Detection of Rolling Element Bearings (Hu *et al.* 2019) [38]	Vibration	Mathematical Morphology and Maxima Distribution based Bandwidth Segmentation, Band-pass Filter Bank	Envelope Spectrum	Fault Characteristic Frequencies	Visual
An automated faults classification method based on binary pattern and neighborhood component analysis using induction motor (Yaman 2021) [73]	Sound	DWT (Symlet 6, L4)	NA	Local Binary Patterns and Neighborhood Component Analysis	Support Vector Machine, K-nearest Neighbors

2.2 Empirical Mode Decomposition Methods

Although wavelet analysis provides many advantages over the Fourier transform, its biggest problem is the selection of proper mother wavelet. In contrast to wavelet analysis, empirical mode decomposition (EMD) is an adaptive algorithm that decomposes a signal into its intrinsic mode functions (IMF) which characterises the local oscillatory nature of the signal. Evidently, each IMF has a center frequency and bandwidth associated with it and, thus, EMD can be used to isolate the resonance band from noise. Appropriate IMF can be selected by calculating the Pearson Correlation Coefficient between the original signal and each IMF [74]. Further analysis can either be carried out in the Hilbert-Huang spectrum or the envelope spectrum of the reconstructed signal. But, EMD suffers with a problem of mode mixing, that is oscillatory modes with different time scale are often assigned to the same IMF or oscillatory modes with same time scale are assigned to different IMFs. To overcome this problem, it is suggested that an ensemble should be taken. Application of Ensemble EMD (EEMD) is reported in [75, 76].

In EEMD, noise is deliberately introduced in the signal and the IMFs obtained for each noise level are ensembled to give mixing-free decomposition of the signal. It is often redundant to add different noise levels and also increases computational load. To avoid this, application of complementary EEMD with adaptive noise (CEEMDAN) is reported in [77, 78]. These works show that the number of ensembles required is significantly less in CEEMDAN. Other methods to overcome the modes mixing problem in EMD are local mean decomposition (LMD) and variational mode decomposition (VMD). LMD decomposes a signal into its constituent product functions (PF) and is found to be effective for bearing fault diagnosis [79, 80]. VMD tries to solve the mode mixing problem and is found better than conventional EMD [81, 82]. Its application is also reported under variable speed conditions [83].

A comparative study of the published works in EMD, LMD, VMD based algorithms, reported in the literature, is given in Table 2.2.

Table 2.2: Review of empirical mode and other decomposition methods (EMD - Empirical Mode Decomposition, LMD - Local Mean Decomposition, VMD - Variational Mode Decomposition, EEMD - Ensemble EMD, CEEMD - Complementary EEMD, CEEMDAN - CEEMD with Adaptive Noise, IMF - Intrinsic Mode Function, PF - Product Function, AR - Auto-Regressive Model, HHT - Hilbert Huang Transform)

Title	**Measurement**	**Decomposition**	**Spectral Analysis**	**Features**	**Classification**
A comparison study of improved Hilbert-Huang transform and wavelet transform: Application to fault diagnosis for rolling bearing (Peng *et al.* 2005) [74]	Vibration	EMD (Optimised Correlation Coefficient)	HHT (Hilbert Spectrum)	Fault Characteristic Frequencies	Visual
A fault diagnosis approach for roller bearings based on EMD method and AR model (Junsheng *et al.* 2006) [84]	Vibration	EMD	NA	AR Model Parameters	Visual
Sifting process of EMD and its application in rolling element bearing fault diagnosis (Dong *et al.* 2009) [85]	Vibration	EMD	Envelope Spectrum of first IMF	Fault Characteristic Frequencies	Visual
An insight concept to select appropriate IMFs for envelope analysis of bearing fault diagnosis (Tsao *et al.* 2012) [86]	Vibration	EMD (Resonance based IMF selection)	Envelope Spectrum	Fault Characteristic Frequencies	Visual
Faulty bearing signal recovery from large noise using a hybrid method based on spectral kurtosis and ensemble empirical mode decomposition (Guo *et al.* 2012) [87]	Vibration	Kurtogram and EEMD (Optimised Correlation Coefficient)	Envelope Spectrum	Fault Characteristic Frequencies	Visual
A fault diagnosis approach for roller bearing based on VPMCD under variable speed condition (Yang *et al.* 2013) [79]	Vibration	Local Mean Decomposition	Order Envelope Spectrum	Fault Characteristic Frequencies	Variable Predictive Model based Class Discriminate
Bearing fault detection based on hybrid ensemble detector and empirical mode decomposition (Georgoulas *et al.* 2013) [88]	Vibration	EMD	HHT (Hilbert Spectrum)	Mean and Standard Deviation of IMFs, Principle Component Analysis	Majority Voting
Ensemble empirical mode decomposition-based teager energy spectrum for bearing fault diagnosis (Feng *et al.* 2013) [75]	Vibration	Ensemble EMD (Correlation based rejection and Kurtosis based selection of IMFs)	Teager Energy Spectrum	Fault Characteristic Frequencies	Visual
Generalized empirical mode decomposition and its applications to rolling element bearing fault diagnosis (Zheng *et al.* 2013) [89]	Vibration	EMD (Adaptive baseline selection)	Envelope Spectrum	Fault Characteristic Frequencies	Visual
Multi-Fault detection of rolling element bearings under harsh working condition using imf-based adaptive envelope order analysis (Zhao *et al.* 2014) [76]	Vibration	Ensemble EMD	Enveloe Order Spectrum	Fault Sensitive Matrix	Thresholding

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Table 2.2 – continued from previous page

Title	Measurement	Decomposition	Spectral Analysis	Features	Classification
Rolling bearing diagnosing method based on empirical mode decomposition of machine vibration signal (Dybała and Zimroz 2014) [90]	Vibration	EMD (Optimised Correlation Coefficient)	Frequency Spectrum	Fault Characteristic Frequencies	Visual
An adaptively fast ensemble empirical mode decomposition method and its applications to rolling element bearing fault diagnosis (Xue *et al.* 2015) [91]	Vibration	Complementary EEMD (Relative Root-Mean-Square Error Optimised)	Envelope Spectrum	Fault Characteristic Frequencies	Visual
Rotating machine fault diagnosis based on intrinsic characteristic-scale decomposition (Li *et al.* 2015) [92]	Vibration	Intrinsic Characteristic-scale Decomposition	Envelop Spectrum	Fault Characteristic Frequencies	Visual
The rolling bearing fault feature extraction based on the LMD and envelope demodulation (Ma *et al.* 2015) [93]	Vibration	Local Mean Decomposition	Envelop Spectrum, Teager Energy Spectrum	Fault Characteristic Frequencies	Visual
A data-driven method to enhance vibration signal decomposition for rolling bearing fault analysis (Grasso *et al.* 2016) [94]	Vibration	EMD (Dissimilarity Index based combined mode function selection)	Envelope Spectrum	Fault Characteristic Frequencies	Visual
Bearing fault diagnosis based on variational mode decomposition and total variation denoising (Zhang *et al.* 2016) [81]	Vibration	Variational Mode Decomposition (majoriation–minization based total variation denoising)	Envelope Spectrum	Fault Characteristic Frequencies	Visual
Multivariate empirical mode decomposition and its application to fault diagnosis of rolling bearing (Lv *et al.* 2016) [95]	Vibration	EMD (Nonlocal means, Correlation Analysis)	Frequency Spectrum	Fault Characteristic Frequencies	Visual
The Fault Feature Extraction of Rolling Bearing Based on EMD and Difference Spectrum of Singular Value (Han *et al.* 2016) [96]	Vibration	EMD (Difference Spectrum of Signular Value for IMF selection)	Envelope Spectrum	Fault Characteristic Frequencies	Visual
Underdetermined blind source separation with variational mode decomposition for compound roller bearing fault signals (Tang *et al.* 2016) [97]	Vibration	VMD (Independent Component Analysis for IMF selection)	Envelop Spectrum	Fault Characteristic Frequencies	Visual
A Frequency-Weighted Energy Operator and complementary ensemble empirical mode decomposition for bearing fault detection (Imaouchen *et al.* 2017) [98]	Vibration	CEEMD (Energy, Kurtosis, Entropy based IMF selection)	Envelop Spectrum	Fault Characteristic Frequencies	Visual

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Table 2.2 – continued from previous page

Title	Measurement	Decomposition	Spectral Analysis	Features	Classification
Low-speed rolling bearing fault diagnosis based on EMD denoising and parameter estimate with alpha stable distribution (Xiong *et al.* 2017) [99]	Vibration	EMD (Kurtosis Optimised)	NA	Alpha-Stable Distribution Parameters	Particle Swarm Optimisation based Support Vector Machines, Minimum Output Coding
Time-frequency representation based on robust local mean decomposition for multicomponent AM-FM signal analysis (Liu *et al.* 2017) [100]	Vibration	Robust LMD based Kurtogram	Envelope Spectrum	Fault Characteristic Frequencies	Visual
Compound fault diagnosis of bearings using improved fast spectral kurtosis with VMD (Wan *et al.* 2018) [101]	Vibration	VMD, Fast Spectral Kurtosis	Envelope Spectrum	Fault Characteristic Frequencies	Visual
Data decomposition techniques with multi-scale permutation entropy calculations for bearing fault diagnosis (Yasir and Koh 2018) [102]	Vibration	LMD	NA	Multi-scale Permutation Entropy	
EEMD-based notch filter for induction machine bearing faults detection (Amirat *et al.* 2018) [103]	Stator Current	EEMD (Correlation based Cancellation)	NA	Statistical Analysis (Chi-Square)	
Rolling Bearing Fault Diagnosis Based on an Improved Denoising Method Using the Complete Ensemble Empirical Mode Decomposition and the Optimized Thresholding Operation (Abdelkader *et al.* 2018) [77]	Vibration	CEEMD with Adaptive Noise (Energy based IMF selection)	Envelop Spectrum	Fault Characteristic Frequencies	Visual
A fault diagnosis method for rotating machinery based on improved variational mode decomposition and a hybrid artificial sheep algorithm (Shan *et al.* 2019) [104]	Vibration	VMD	NA	Energy, Root-Mean-Square, Singular Values, Artificial Sheep Algorithm	Support Vector Machine
A modified scale-space guiding variational mode decomposition for high-speed railway bearing fault diagnosis (Huang *et al.* 2019) [105]	Vibration	Modified Scale-Space VMD (Selection of Number of Decompositions and Penalty Factor)	Envelope Spectrum	Fault Characteristic Frequencies	Visual
A New Feature Extraction Method for Bearing Faults in Impulsive Noise Using Fractional Lower-Order Statistics (Xu and Liu 2019) [106]	Vibration	LMD	NA	Fractional Lower Order Statistics and Low Dimensional Mapping Matrix	K-means Clustering
An improved complementary ensemble empirical mode decomposition with adaptive noise and its application to rolling element bearing fault diagnosis (Cheng *et al.* 2019) [78]	Vibration	Complementary CEEMDAN	Minimum Entropy Deconvolution and Envelope Spectrum	Fault Characteristic Frequencies	Visual

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Table 2.2 – continued from previous page

Title	**Measurement**	**Decomposition**	**Spectral Analysis**	**Features**	**Classification**
Improving the accuracy of fault frequency by means of local mean decomposition and ratio correction method for rolling bearing failure (Duan *et al.* 2019) [107]	Vibration	LMD (Correlation based PF selection)	Envelope Spectrum (Ratio Correction)	Fault Characteristic Frequencies	Visual
Multi-Bandwidth Mode Manifold for Fault Diagnosis of Rolling Bearings (Jiang *et al.* 2019) [108]	Vibration	VMD	NA	Multi-bandwidth Mode Manifold, Local Tangent Space Alignment, Gini Index	Visual
Optimized LMD method and its applications in rolling bearing fault diagnosis (Xu *et al.* 2019) [80]	Vibration	Optimised LMD (Spectral Negentropy Termination, Order Statistics based Local Envelopes)	Envelope Spectrum	Fault Characteristic Frequencies	Visual
An optimized VMD method and its applications in bearing fault diagnosis (Li *et al.* 2020) [109]	Vibration	VMD (Frequency Band Entropy based IMF selection)	Envelope Spectrum	Fault Characteristic Frequencies	Visual
Compound bearing fault detection under varying speed conditions with virtual multichannel signals in angle domain (Tang *et al.* 2020) [83]	Vibration	Resampling, VMD, Independent Component Analysis	Envelope Order Spectrum	Fault Characteristic Frequencies	Visual
Optimal IMF selection and unknown fault feature extraction for rolling bearings with different defect modes (Yang *et al.* 2020) [110]	Vibration	EEMD (Spectral Amplificatio Factor for IMF selection)	NA	Piecewise Mean Value Feature	
The VMD-scale space based hoyergram and its application in rolling bearing fault diagnosis (Shi *et al.* 2020) [82]	Vibration	VMD, Hoyer Index based Kurtogram	Envelope Spectrum	Fault Characteristic Frequencies	Visual

2.3 Fractional Domain Methods

Bearing fault signals encapsulate a complex interaction between different machine components. The envelope spectrum, wavelet decomposition and intrinsic mode decomposition methods are advantageous, but are sometime not enough. In light of this, fractional domain generalisations of the signal processing algorithms provide an extra dimension over which the performance of fault diagnosis can be improved. Several fractional time-frequency representations (TFR) are proposed and their application for bearing fault diagnosis is discussed in [111–114]. The fractionality introduced in these is mainly due to the lower-order distribution representation of the bearing signal. Such TFRs are found to provide better resolution and noise resistance compared to their conventional counterparts. A blind source separation algorithm is also proposed based on one of these representations [112].

Another type of fractional processing is introduced in [115], in which the system resonance is modelled using a fractional order differential equation. The parameters of this equation are estimated from theoretical values of the fault characteristic frequencies and the estimated bearing signature, in comparison, to the actual signal is found to diagnose the occurrence of the fault. In [116], a generalisation of conventional envelope analysis is applied for bearing fault diagnosis. Finally, application of 1.5 dimensional spectrum for bearing fault diagnosis is proposed in [117, 118]. Such a spectrum is a generalisation between the conventional power spectral density (PSD) and the bispectrum of a signal. PSD is obtained by taking Fourier transform of the autocorrelation of the signal and is related to signal variance, whereas the bispectrum of the signal is the Fourier transform of a third order cummulant taken across two frequency axes. It is related to the skewness of the signal. The concept of 1.5-dimensional spectrum arises from the third order cumulant along the single frequency axis. A repetitive application of such a transformation is found to be beneficial for bearing fault diagnosis [118], whereas the review on cyclic bispectrum is done in next subsection on cyclostationarity analysis.

Table 2.3 gives a review of relevant papers on fractional domain methods.

Table 2.3: Review of fractional domain processing (SVD - Singular Value Decomposition, GA - Genetic Algorithm, FCF - Fault Characteristic Frequency)

Title	**Measurement**	**Decomposition**	**Spectral Analysis**	**Features**	**Classification**
Rolling bearing fault detection using an adaptive lifting multiwavelet packet with a 1 1/2 dimension spectrum (Jiang *et al.* 2013) [117]	Vibration	Adaptive Lifting Multiwavelet Packet Transform (SVD Entropy and GA Optimised, L8)	1.5 Dimension Spectrum	Fault Characteristic Frequencies	Visual
Applications of fractional lower order time-frequency representation to machine bearing fault diagnosis (**Frac2017Long** 2017) [**Frac2017Long**]	Vibration	Fractional Lower Order Time-Frequency Representations	Time-Frequency Represntation	Fault Characteristic Frequencies	Visual

Continued on next page

Table 2.3 – continued from previous page

Title	Measurement	Decomposition	Spectral Analysis	Features	Classification
Fractional envelope analysis for rolling element bearing weak fault feature extraction (Wang *et al.* 2017) [116]	Vibration	Fractional Hilbert Transform	Fractional Envelope Spectrum	Fault Characteristic Frequencies, Kurtosis	Visual
A WHT Signal Detection-Based FLO-TF-UBSS Algorithm Under Impulsive Noise Environment (Long *et al.* 2018) [112]	Vibration	Fractional Lower Order Pseudo Wigner-Hough Transform	Time-Frequency Represntation	Fault Characteristic Frequencies	Visual
Applications of fractional lower order frequency spectrum technologies to bearing fault analysis (Long *et al.* 2019) [113]	Vibration	Fractional Lower Order Time-Frequency Representations	Time-Frequency Represntation	Fault Characteristic Frequencies	Visual
Weak signal enhancement by fractional-order system resonance and its application in bearing fault diagnosis (Wu *et al.* 2019) [115]	Vibration	Fractional Order System Resonance Model	FFT	Fault Characteristic Frequencies	Visual
Applications of Fractional Lower Order Synchrosqueezing Transform Time Frequency Technology to Machine Fault Diagnosis (Wang and Long 2020) [114]	Vibration	Fractional Lower Order Synchrosqueezing Transform	Time-Frequency Represntation	Fault Characteristic Frequencies	Visual
Bearing fault diagnosis based on iterative 1.5-dimensional spectral kurtosis (Zhang *et al.* 2020) [118]	Vibration	WPT of signal obtained after 3 iterations of Teager Energy Operation and 1.5D Spectrum	Envelope Spectrum	Fault Characteristic Frequencies	Visual

2.4 Cyclostationarity Based Methods

Bearing fault signature shows complex modulation due to the high-frequency resonance and low-range fault characteristic frequency. For correctly diagnosing the fault, it is imperative that such hidden periodicity is amply revealed in the spectrum. Conventional power spectral density (PSD) assumes that the signal is stationary and thus fails to bring out the fault signature. Thus, application of cyclostationary analysis was proposed for bearing fault diagnosis [119]. In particular, bearing fault signals were characterised as second-order cyclostationary processes, which have periodic autocorrelation. Being periodic, the autocorrelation of such signals can be represented using Fourier series coefficients which constitute the *cyclic autocorrelation* of the signal.

A review of the published work on cyclostationarity analysis for bearing fault diagnosis is given in Table 2.4 and it reveals that cyclic autocorrelation is prevalently used as a signal processing tool. Just as the PSD can be calculated from the conventional autocorrelation, the Fourier transform of the cyclic autocorrelation gives spectral correlation density (SCD). The application of SCD and degree of cyclostationarity (DCS) for rotating machines is proposed in [119]. This idea is elaborated in [120] and it is shown that by taking the quadratic transform, the hidden periodicity is converted to first-order periodicity and revealed in the PSD. This fundamental concept is further explored in [121] and the conventional envelope spectrum is shown to be a specific case of the DCS spectrum. This lays down the foundation for the application of squared envelope spectrum (SES), which is now a common practice for bearing fault diagnosis.

The research on cyclostationarity analysis has served three important purposes. First, it has created a sound theoretical foundation for bearing fault diagnosis and justified the use of envelope analysis [119–121]. Second, it has created a framework for fault diagnosis using spectral correlation density (SCD) [122–124], which was further extended to higher order analysis in [125–127]. Third, it has paved a way for defining cyclostationarity based fault indices, which can be used to guide the denoising or source separation algorithms [128–132].

It should be noted that fault analysis using SCD, or its higher order counterparts, is not straightforward. These spectra are often computationally expensive, difficult to interpret and can not be used directly for automatic fault diagnosis. Also, for fault diagnosis under variable speed conditions, the signal has to be resampled before calculating its SCD [124]. However, the performance of cyclostationarity analysis is found to be better compared to other methods [133].

Table 2.4: Review of cyclostationarity analysis (FCF - Fault Characteristic Frequency)

Title	Measurement	Decomposition	Spectral Analysis	Features	Classification
Cyclostationarity in rotating machine vibrations (McCormick and Nandi 1998) [119]	Vibration	Cyclic autocorrelation with cycle frequency	Degree of Cyclostationarity Spectrum, Spectral Correlation Density	Fault Characteristic Frequencies	Visual
Cyclostationary analysis of rolling-element bearing vibration signals (ANTONIADIS and GLOSSIOTIS 2001) [120]	Vibration	Cyclic autocorrelation with cycle frequency	Degree of Cyclostationarity Spectrum, Spectral Correlation Density	Fault Characteristic Frequencies	Visual
Differential diagnosis of gear and bearing faults (Antoni and Randall 2002) [122]	Vibration	Cyclic autocorrelation with cycle frequency equal to shaft speed	Spectral Correlation Density	Fault Characteristic Frequencies	Visual
Cyclic statistics in rolling bearing diagnosis (Li and Qu 2003) [123]	Vibration	Cyclic Autocorrelation	Cyclic Spectrum (Selection of band of cyclic frequency)	Fault Characteristic Frequencies	Visual
Novel cyclostationarity-based blind source separation algorithm using second order statistical properties: Theory and application to the bearing defect diagnosis (Bouguerriou *et al.* 2005) [128]	Vibration	Cyclic Autocorrelation Based Cost Function and Blind Source Separation	NA	Fault Characteristic Frequencies	Visual
Cyclic bispectrum patterns of defective rolling element bearing vibration response (Yiakopoulos and Antoniadis 2006) [125]	Vibration	Cyclic Autocorrelation	Cyclic Bispectrum	Fault Characteristic Frequencies	Visual
A feature extraction method based on information theory for fault diagnosis of reciprocating machinery (Wang and Chen 2009) [134]	Vibration	Symptom Information Wave	Envelope Spectrum	Fault Characteristic Frequencies	Visual
Cyclostationarity of Acoustic Emissions (AE) for monitoring bearing defects (Kilundu *et al.* 2011) [129]	Acoustic Emission	Cyclic Autocorrelation	Spectral Correlation Density	Fault Characteristic Frequencies, Integrated Spectral Correlation (for fault size)	Visual
Wigner-Ville distribution based on cyclic spectral density and the application in rolling element bearings diagnosis (Zhou *et al.* 2011) [126]	Vibration	Cyclic Autocorrelation	WVD based on CSD	Fault Characteristic Frequencies	Visual
Application of the horizontal slice of cyclic bispectrum in rolling element bearings diagnosis (Zhou *et al.* 2012) [127]	Vibration	Cyclic Autocorrelation	Horizontal Slice of Cyclic Bispectrum	Fault Characteristic Frequencies	Visual
Cyclostationarity applied to acoustic emission and development of a new indicator for monitoring bearing defects (Kedadouche *et al.* 2014) [130]	Acoustic Emission	Cyclic Autocorrelation	Spectral Correlation Density	Fault Characteristic Frequencies, Integrated Spectral Correlation based Indices	Visual

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Table 2.4 – continued from previous page

Title	Measurement	Decomposition	Spectral Analysis	Features	Classification
Angle-time cyclostationarity for the analysis of rolling element bearing vibrations (Abboud *et al.* 2015) [124]	Vibration	Resampling and Cyclic Autocorrelation	Spectral Correlation Density	Fault Characteristic Frequencies	Visual
A comparison of cepstral editing methods as signal pre-processing techniques for vibration-based bearing fault detection (Peeters *et al.* 2017) [135]	Vibration	Cepstral Editing	Squared Envelope Spectrum (SES)	SES Feature	Visual
Blind deconvolution based on cyclostationarity maximization and its application to fault identification (Buzzoni *et al.* 2018) [131]	Vibration	Cyclostationary Blind Deconvolution	NA	Fault Period, Integrated Cyclic Spectrum based cost function for deconvolution	Visual
Weighted Cyclic Harmonic-to-Noise Ratio for Rolling Element Bearing Fault Diagnosis (Mo *et al.* 2020) [132]	Vibration	Filter Bank	Squared Envelope Spectrum (SES)	Fault Characteristic Frequencies, Weighted Cyclic Harmonic-to-Noise Ratio (for filter band selection)	Visual

2.5 Order Tracking Methods

The incipient bearing faults can be diagnosed in envelope spectrum using the fault characteristic frequencies (FCF). These FCF values depend on bearing geometry and the rotational speed. Speed fluctuations are very common, particularly, during start-up and shut-down operations or load variations. Under speed variations, bearing fault signals become completely non-stationary. Broadly, there are two approaches to diagnose faults under varying speed conditions, order tracking and instantaneous frequency estimation using time-frequency representation. Once the speed is measured, the vibration signal can be resampled and converted to the angle domain, in which the frequency components represent multiples of rotational speed or fault characteristic orders (FCO) [136]. An order spectrum thus obtained readily gives the information about the location of fault in the bearing. This method is known as order tracking and can be implemented in either hardware or software [137]. But, the hardware required for adaptive resampling is expensive and unreliable, thus, the focus of the research has shifted towards the computed order tracking.

A review of relevant work on different order tracking related algorithms is given in Table 2.5. It shows that almost every signal processing method, discussed earlier, is used with resampling for fault diagnosis under variable speed conditions - wavelet [138, 139], EMD [140], VMD [83], STFT [139, 141], Cepstrum Analysis [142, 143]. A detailed analysis of computed order tracking shows that it is highly sensitive to the timing accuracy of resampling and the order of interpolation used [136]. Other modifications of conventional order tracking are also reported, like hybrid order tracking [144] and iterative enveloping followed by low-pass filtering to improve the fault features [145].

Another disadvantage of order tracking is its inability to perform tacholess fault diagnosis. Several modifications of conventional order tracking are reported to overcome this disadvantage. These techniques mainly use an additional step of extracting the speed information from the time-frequency representation (TFR) of the signal, but the actual fault diagnosis is carried out using order tracking. Extraction of speed curve from the TFR can be carried out using direct local maximum ridge detection (DMRD) [146], cost function based ridge detection (CFRD) [147, 148], dynamic path optimization based ridge detection (DPORD) [149], tunable E-factor based ridge detection (TERD) [150]. Each of these methods is a modification of its predecessor. Tacholess order-tracking of current signals is proposed in [151]. All of these methods resample the bearing signal using the speed curve extracted from the TFR. However, as claimed in [152, 153], use of order tracking is not necessary if multiple ridge curves are extracted from the TFR.

Table 2.5: Review of order tracking analysis (FCF - Fault Characteristic Frequency, EMD - Empirical Mode Decomposition, STFT - Short Time Fourier Transform, CWT - Continuous Wavelet Transform

Title	Measurement	Decomposition	Spectral Analysis	Features	Classification
Bearing fault detection and diagnosis based on order tracking and Teager-Huang transform (Li *et al.* 2010) [140]	Vibration	EMD, Discrete Energy Separation Algorithm	Teager-Huang Order Spectrum	Fault Characteristic Order	Visual
Order bi-spectrum for bearing fault monitoring and diagnosis under run-up condition (Li 2011) [154]	Vibration	Resampling and Hilbert Transform	Order Bi-spectrum	Fault Characteristic Order	Visual

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Table 2.5 – continued from previous page

Title	Measurement	Decomposition	Spectral Analysis	Features	Classification
Application of cepstrum pre-whitening for the diagnosis of bearing faults under variable speed conditions (Borghesani *et al.* 2013) [142]	Vibration	Order Tracking and Synchronous Averaging, Cepstrum Pre-whitening	Squared Envelope Order Spectrum	Fault Characteristic Order	Visual
Rotating speed isolation and its application to rolling element bearing fault diagnosis under large speed variation conditions (Wang *et al.* 2015) [155]	Vibration	Fast Kurtogram	Spectrogram	Fault Characteristic Order, Ridge Detection	Visual
Rolling element bearing defect diagnosis under variable speed operation through angle synchronous averaging of wavelet de-noised estimate (Mishra *et al.* 2016) [138]	Vibration	Resampling, Wavelet Denoising, Angle Synchronous Averaging	Envelope Order Spectrum	Fault Characteristic Order	Visual
Bearing fault diagnosis under variable rotational speed via the joint application of windowed fractal dimension transform and generalized demodulation: A method free from prefiltering and resampling (Shi *et al.* 2016) [141]	Vibration	Windowed Fractal Dimension Transform, STFT and Generalised Demodulation	Order Spectrum	Fault Characteristic Order	Visual
Specialization improved nonlocal means to detect periodic impulse feature for generator bearing fault identification (Chen *et al.* 2017) [156]	Vibration	Resampling, Specialisation Improved Modified Nonlocal Means Denoising	Envelope Order Spectrum	Fault Characteristic Order	Visual
A PLL-based resampling technique for vibration analysis in variable-speed wind turbines with PMSG: A bearing fault case (Pezzani *et al.* 2017) [157]	Vibration	Phase Locked Loop based Resampling	Order Spectrum	Fault Characteristic Order	Visual
Bearing fault diagnosis under unknown time-varying rotational speed conditions via multiple time-frequency curve extraction (Huang *et al.* 2018) [158]	Vibration	STFT	Spectrogram	Ridge Detection, Fault Characteristic Ratios	Thresholding
A New Methodology to Estimate the Rotating Phase of a BLDC Motor with Its Application in Variable-Speed Bearing Fault Diagnosis (Lu and Wang 2018) [159]	Vibration	Resampling and Hilbert Transform (Optimised with Sinusoid Similarity)	Envelope Order Spectrum	Fault Characteristic Order	Visual
High-accuracy fault feature extraction for rolling bearings under time-varying speed conditions using an iterative envelope-tracking filter (Chen *et al.* 2019) [160]	Vibration	Iterative Envelope Tracking Filter	Time-Frequency Representation	Fault Characteristic Order	Visual

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Table 2.5 – continued from previous page

Title	Measurement	Decomposition	Spectral Analysis	Features	Classification
A Two-Stage Method Using Spline-Kernelled Chirplet Transform and Angle Synchronous Averaging to Detect Faults at Variable Speed (Wang and Xiang 2019) [161]	Vibration	Chirplet Transform (Spline Kernel), Resampling, Angle Synchronous Averaging	Order Spectrum	Fault Characteristic Order	Visual
Bearing fault diagnosis under time-varying rotational speed via the fault characteristic order (FCO) index based demodulation and the stepwise resampling in the fault phase angle (FPA) domain (Wang and Chu 2019) [139]	Vibration	Band-pass Filtering (Fault Characteristic Order Index Optimised), STFT and CWT Curves Extraction and Resampling	Envelope Order Spectrum	Fault Characteristic Order	Visual
Order spectrogram visualization for rolling bearing fault detection under speed variation conditions (Wang *et al.* 2019) [162]	Vibration	Band-pass Filtering (Fault Characteristic Order Index Optimised), STFT Curves Extraction and Resampling	Envelope Order Spectrum	Fault Characteristic Order	Visual
Fault diagnosis of rolling bearing under fluctuating speed and variable load based on TCO Spectrum and Stacking Auto-encoder (Xiang *et al.* 2019) [163]	Vibration	Teager Energy Demodulation, Resampling	Envelope Order Spectrum	NA	Stacking Auto-Encoder
Multi-band identification for enhancing bearing fault detection in variable speed conditions (Klausen *et al.* 2020) [143]	Vibration	Resampling, Cepstrum Pre-whitening	Envelope Order Spectrum	Fault Characteristic Order	Visual

2.6 Summary

There is a wide pool of articles available in the field of bearing fault diagnosis. A brief review of literature focussing on important signal processing tools is carried out. The details of the fault diagnosis algorithm, in comparison with Fig 1.2, are tabulated chronologically and evolution of such techniques is discussed. Amongst all the signal processing techniques, wavelet analysis is thoroughly explored. Several articles try to address the key issues regarding the wavelets - base wavelet selection, selection of optimum scale or node, maximum level of decomposition, type of wavelet transform used, application specific design of the wavelets *et cetra*. However, due to the shear simplicity, empirical mode decomposition has gained popularity and to overcome its key problem of mode mixing, several modifications, Ensemble EMD, Complementary EEMD, variational mode decomposition (VMD) are suggested. VMD, however, suffers from the problem of parameter selection.

On the other hand, very little research is found in fractional domain processing. The fractional domain generalisations of existing signal processing methods provide an extra degree of freedom over which the performance of the method can be improved. Hence, the first algorithm proposed in this thesis focuses on this aspect. The second proposed algorithm, on the other hand, focuses on the cyclostationary nature of bearing signal. In the available literature, the cyclostationarity is explored rather theoretically, but is often found practically difficult to interpret because of the complex nature of signal representation. However, the cyclic changes in the statistics is an inherent characteristic of bearing fault signals and can be explored further to achieve practically efficient fault diagnosis algorithms.

2.7 Gaps in Existing Research

After the study of available literature, following gaps are identified -

1. A common framework for fault diagnosis under constant as well as variable speed conditions needs to be further explored.
2. Although wavelets are widely explored in the literature, choice of wavelet significantly affects the accuracy of such methods. Thus ideally the fault diagnosis framework should be independent of wavelet selection.
3. The choice of fault features to select optimum demodulation band may badly affect the overall accuracy. Kurtosis and other sparsity indices are often used for this purpose, but their accuracy is poor.
4. Fractional domain methods have a potential of maximising the fault features, but is not given enough attention in the literature.

5. A dataset of acoustic signals is not publicly available for bearing fault diagnosis. The dataset for variable speed conditions is made available in 2018. All the cases of this dataset are not yet explored in the literature apart from the benchmark method.
6. Rolling element faults are still the most elusive type of faults. Many cases of such faults can not be adequately diagnosed using state of the art techniques.