**AFRL-RX-WP-TP-2008-4309**

# FEATURE EXTRACTION FOR BEARING PROGNOSTICS AND HEALTH MANAGEMENT (PHM)–A SURVEY (PREPRINT)

**Weizhong Yan, Hai Qiu, and Naresh Iyer**

**Metals Branch**
**Metals, Ceramics, and NDE Division**

**MAY 2008**

**STINFO COPY**

**AIR FORCE RESEARCH LABORATORY**
**MATERIALS AND MANUFACTURING DIRECTORATE**
**WRIGHT-PATTERSON AIR FORCE BASE, OH 45433-7750**
**AIR FORCE MATERIEL COMMAND**
**UNITED STATES AIR FORCE**

# REPORT DOCUMENTATION PAGE

| 1. REPORT DATE *(DD-MM-YY)* | 2. REPORT TYPE | 3. DATES COVERED *(From - To)* |
|---|---|---|
| May 2008 | Conference Proceedings Preprint | |

**4. TITLE AND SUBTITLE**

FEATURE EXTRACTION FOR BEARING PROGNOSTICS AND HEALTH MANAGEMENT (PHM)–A SURVEY (PREPRINT)

**5a. CONTRACT NUMBER**
In-house

**5b. GRANT NUMBER**

**5c. PROGRAM ELEMENT NUMBER**
62102F

**6. AUTHOR(S)**

Weizhong Yan (Industrial Artificial Intelligence Lab)
Hai Qiu and Naresh Iyer (AFRL/RXLMN)

**5d. PROJECT NUMBER**
4347

**5e. TASK NUMBER**
RG

**5f. WORK UNIT NUMBER**
M02R3000

**7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)**

Industrial Artificial Intelligence Lab

Metals Branch (AFRL/RXLMN)
Metals, Ceramics, and NDE Division
Materials and Manufacturing Directorate
Wright-Patterson Air Force Base, OH 45433-7750
Air Force Materiel Command, United States Air Force

**8. PERFORMING ORGANIZATION REPORT NUMBER**
AFRL-RX-WP-TP-2008-4309

**9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)**

Air Force Research Laboratory
Materials and Manufacturing Directorate
Wright-Patterson Air Force Base, OH 45433-7750
Air Force Materiel Command
United States Air Force

**10. SPONSORING/MONITORING AGENCY ACRONYM(S)**
AFRL/RXLMN

**11. SPONSORING/MONITORING AGENCY REPORT NUMBER(S)**
AFRL-RX-WP-TP-2008-4309

**12. DISTRIBUTION/AVAILABILITY STATEMENT**
Approved for public release; distribution unlimited.

**13. SUPPLEMENTARY NOTES**
Conference proceedings submitted to the 62nd Meeting of the Society for Machinery, Virginia Beach, VA, 06 May 2008.

PAO Case Number:  WPAFB 08-2959; Clearance Date: 17 Apr 2008. The U.S. Government is joint author of this work and has the right to use, modify, reproduce, release, perform, display, or disclose the work. Paper contains color.

**14. ABSTRACT**

Feature extraction in bearing PHM involves extracting characteristic signatures from the original sensor measurements, which are sensitive to bearing conditions and thus most useful in determining bearing faults. The quality of extracted features directly affects the performance and the effectiveness of bearing PHM. Feature extraction is therefore a critical component in bearing PHM. To optimally improve PHM effectiveness and minimize maintenance costs of bearings, a large amount research has been conducted in extracting salient features for PHM, which leads to a considerable number of feature extraction techniques. Our main effort in this paper is to survey some major techniques explored so far, focusing on more recent advancements. Our endeavor also includes pointing out the advantages and disadvantages of each of those techniques. This paper attempts to serve as a general reference for bearing PHM practitioners and as a general guide for choosing proper feature extraction methods for bearing PHM systems.

**15. SUBJECT TERMS**
bearing, feature extraction, diagnosis, prognosis, health management, vibration analysis

| 16. SECURITY CLASSIFICATION OF: | | | 17. LIMITATION OF ABSTRACT: | 18. NUMBER OF PAGES | 19a. NAME OF RESPONSIBLE PERSON (Monitor) |
|---|---|---|---|---|---|
| **a. REPORT** Unclassified | **b. ABSTRACT** Unclassified | **c. THIS PAGE** Unclassified | SAR | 18 | James M. Larsen |

19b. TELEPHONE NUMBER *(Include Area Code)*
N/A

# FEATURE EXTRACTION FOR BEARING PROGNOSTICS AND HEALTH MANAGEMENT (PHM) – A SURVEY

**Weizhong Yan**, Hai Qiu, and Naresh Iyer

Industrial Artificial Intelligence Lab
GE Global Research Center
One Research Circle
Niskayuna, NY 12309
*{yan, qiu, & Iyerna} @ crd.ge.com*

**Abstract**: Feature extraction in bearing PHM involves extracting characteristic signatures from the original sensor measurements, which are sensitive to bearing condition and thus most useful in determining bearing faults. The quality of extracted features directly affects the performance and the effectiveness of bearing PHM. Feature extraction is therefore a critical component in bearing PHM. To optimally improve PHM effectiveness and minimize maintenance costs of bearings, a large amount research has been conducted in extracting salient features for PHM, which leads to a considerable number of feature extraction techniques. Our main effort in this paper is to survey some major techniques explored so far, focusing on more recent advancements. Our endeavor also includes pointing out the advantages and disadvantages of each of those techniques. This paper attempts to serve as a general reference for bearing PHM practitioners and as a general guide for choosing proper feature extraction methods for bearing PHM systems.

**Keywords:** Bearing; Feature extraction; Diagnosis; Prognosis; Health Management; Vibration Analysis

**1. Introduction:** Prognostics and health maintenance (PHM) is a new maintenance concept/ paradigm. PHM and its sibling, condition-based maintenance (CBM), are the result of maintenance industry's "paradigm shift" from traditional time-based maintenance to support more cost-effective maintenance. While both PHM and CBM use machinery run-time data to determine asset condition, which is then used to schedule required repair and maintenance prior to breakdown, PHM differs CBM in that PHM has the capability of predicting future health, including remaining useful life (RUL) [21]. It is this predictive capability that makes PHM most effective in reducing operational and support (O&S) cost and life-cycle total ownership cost (TOC).

Bearings are one of the most common components in modern rotating machinery. Bearing failures are considered to be the leading culprit of breakdowns in rotating machinery and have resulted in a significant increase of O&S cost. As a tool of effectively preventing unexpected bearing failures, meanwhile maximizing bearing uptime, bearing PHM can significantly reduce O&S cost and improves safety of machinery. As a result, bearing PHM technologies are evolving rapidly in recent years and have attracted tremendous research attention.

Figure 1 illustrates the overall structure of a typical bearing PHM system. It consists of three essential modules, namely, sensing, feature identification, and PHM. The PHM module of bearing PHM systems typically consists of core functions, such as, anomaly detection, fault diagnosis, prognosis, and decision-making. Sensors in the sensing module of a bearing PHM

system can be several types, including vibration, temperature, chemical, acoustic emission, and sound pressure [12]. For real-world PHM systems, raw sensor measurements are rarely used directly by PHM functions. Instead, the raw sensor measurements are preprocessed (filtering, de-noising etc); more importantly, signatures are always extracted from the raw sensor measurements and those signatures that are most sensitive to bearing condition and thus most useful in determining bearing faults are further selected for PHM functions. So preprocessing, feature extraction, and feature selection functions constitute feature ID module that essentially "converts" sensor measurements to information that are more effective, accurate and reliable for PHM functions. Thus feature ID module has been regarded as a critical part of bearing PHM systems.

Identifying salient features for bearing PHM poses challenges. Firstly, various types of sensors with different characteristics (data type, sampling rate, signal-to-noise ratio, etc) may be involved in a bearing PHM system. Identifying salient features from such large amount of sensory data can be difficult. Then, individual functions (detection, diagnosis, and prognosis) of the PHM module have their own metrics for measuring feature goodness. Feature selection in the feature ID module thus needs to take into account the fact that a set of features that are good for one PHM function (e.g., diagnosis) may not necessarily be good for another (e.g., prognosis). That is, feature selection is PHM function-dependent.
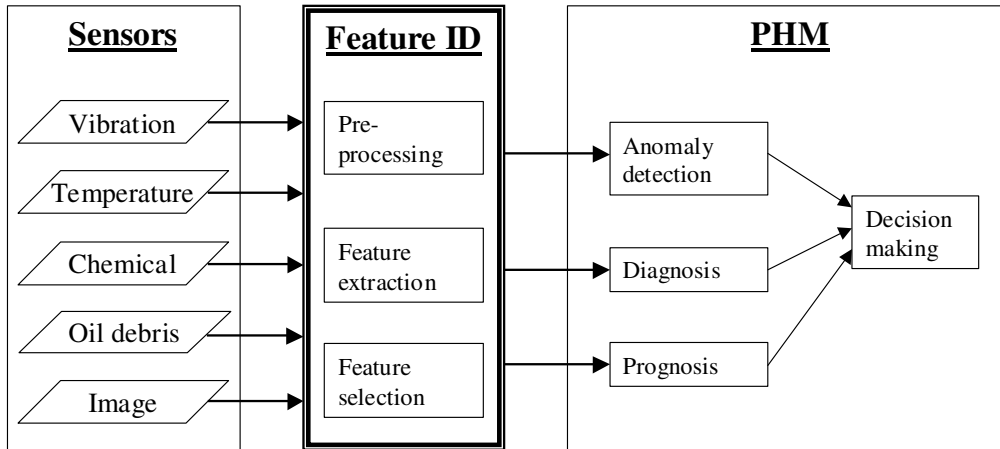


Figure 1: Overall structure of a typical bearing PHM system

Both the importance and the challenges of identifying salient features in bearing PHM have inspired great research interest, thus resulting in a large number of feature extraction methods. For vibration data alone, a large number of feature extraction methods have been proposed, ranging from those using traditional spectral analysis, to those using wavelet analysis [23][24], to those using more advanced signal processing techniques [15][18][2].

With such a large number of feature extraction methods in the literature, a proper categorization that serves as an overview of feature extraction methods and provides a general guidance on properly choosing FE method for specific applications is necessary. However, to the best of our knowledge, such categorization/review work devoted specifically to feature extraction for bearing PHM has not been done. The closest work in this context would be [25], where a subsection of the paper was devoted to summarizing waveform data analysis techniques. This paper attempts to survey some major feature extraction techniques, focusing on more recent development.

In this paper, due to space limitation, we limit our effort to vibration signal only. In other words, we focus on reviewing vibration-based feature extraction methods. It is our intention to publish in a separate paper on a more comprehensive review of techniques associated with all three feature ID functions (preprocessing, FE, and FS) and covering all types of bearing sensor measurements.

The rest of this paper is organized as follows. Section 2 gives some fundamentals of bearings. Different feature extraction methods are discussed and categorized in Section 3. Section 4 concludes the paper.

**2. Bearing fundamentals:** One of the basic purposes of a bearing is to provide a frictionless environment to support and guide a rotating shaft. There are many different ways to classify bearing types, based on their application, material, and lubrication mechanism etc. Typically, bearings can be classified into three general categories based on their construction: fluid film, rolling element, and electromagnetic. This categorization excludes some bearing types, such as air bearings, which are only used in special applications. Some of the feature extraction techniques we surveyed in this paper may be applicable to all types of bearings. Our focus in this paper, however, is on rolling element bearings only.

Rolling element bearings often work well in non-ideal conditions, but sometimes minor problems cause bearings to fail quickly and mysteriously. For example, with a stationary load, small vibrations can gradually press out the lubricant between the races and rollers or balls, and eventually lead to bearing failure due to lack of lubrication.

After nearly four decades of studies on bearing failure mechanism, the theoretical aspects of bearing failure modes are a well-undestood subject. There are three usual limits to the lifetime or load capacity of a bearing: abrasion, fatigue and pressure-induced welding [55][56]. Abrasion is when the surface is eroded by hard contaminants scraping at the bearing materials. Fatigue is when a material breaks after it is repeatedly loaded and released. Pressure-induced welding is when two metal pieces are pressed together at very high pressure and they become one.

Although there are many other apparent causes of bearing failure, most can be reduced to these three. For example, a bearing which is run dry of lubricant fails not because it is "without lubricant", but because lack of lubrication leads to fatigue and welding, and the resulting wear debris can cause abrasion. Similar events occur in false brinelling damage. In high speed applications, the oil flow also reduces the bearing metal temperature by convection. The oil becomes the heat sink for the friction losses generated by the bearing.

A rolling element bearing has four major components, outer race, inner racer, rolling elements (ball, roller, needle etc.), and cage. All four components might be damaged during operation. Generally, the signature of a damaged bearing consists of exponentially decaying ringing that occurs periodically at the characteristic frequency. The vibration signal of a defective bearing usually considers being amplitude modulated at characteristic defect frequency. Matching the measured vibration spectrum with the defect characteristic frequency enables defect detection and enables diagnosis on the defective area [52][53][54].

**3. Feature extraction techniques:** There is no unique way to categorize feature extraction methods used for bearing PHM. Figure 2 shows our taxonomy of vibration-based feature extraction methods. The primary division of vibration-based feature extraction methods is on weather or not the feature extraction method can deal with non-stationary signals.
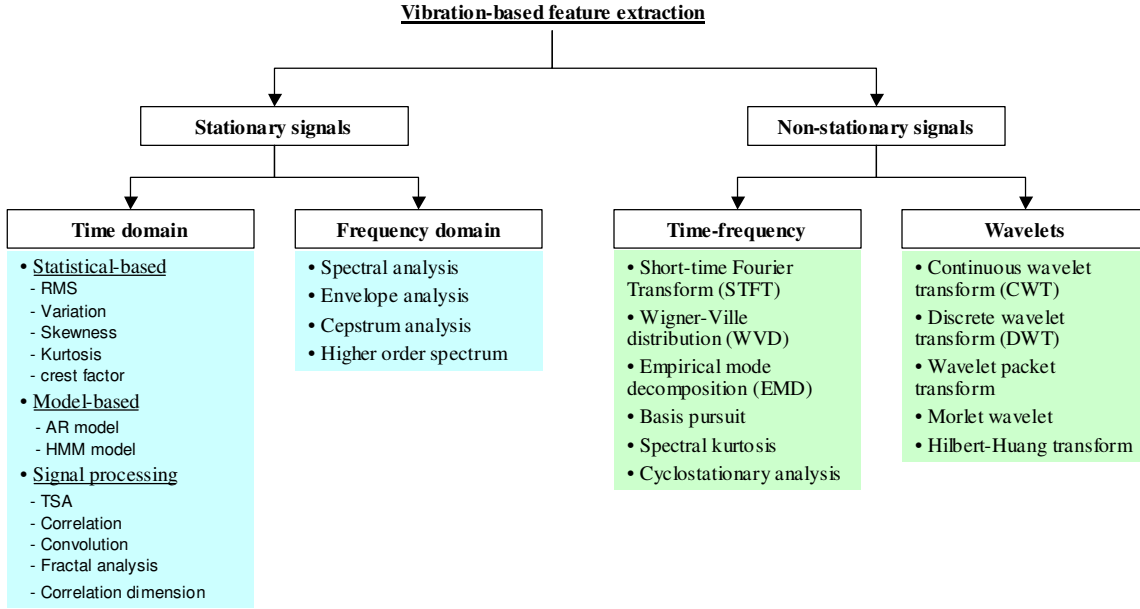
Figure 2: Taxonomy of vibration-based feature extraction methods

**3.1. Stationary signals:** Vibration signals acquired from bearings can be either stationary or non-stationary. While stationary signals are characterized by time-invariant statistical properties, such as the mean value, statistical properties of a non-stationary signal change over time. Vibration signals from real-world bearings are almost always non-stationary since bearings are inherently dynamic (e.g., speed and load condition change over time). However, non-stationary signals are often approximated as stationary, especially within a short time window, for computational convenience. For stationary signals, there are time-domain and frequency-domain techniques for feature extraction.

**3.1.1. Time domain techniques:** When rolling elements of bearing pass the defect location, wide band impulses are generated. And those impulses will then excite some of the vibrational modes of the bearing and its supporting structure. The excitation will result in the sensed vibration signals (waveforms) different in either the overall vibration level or the vibration magnitude distribution, comparing to those under fault-free condition. Time-domain feature extraction is to identify the signatures from the sensed time-domain waveforms (vibration signals and/or acoustic emissions), which are sensitive to bearing conditions. Depending on what underlying technology is used, time-domain feature extraction techniques can be further categorized into three groups: statistical-based, model-based, and signal processing-based approaches, all three of which are detailed as follows.

**a) Statistical-based approaches:** One of the most traditional time-domain feature extraction methods is to calculate descriptive statistics of vibration signals, including those measuring power content of vibration signals, such as the root mean square (RMS); those measuring signal magnitude and pattern, such as, the peaks, the peak-to-peak intervals, the crest factor; and those measuring signal distribution, such as, the mean ($1^{st}$ moment), the variance ($2^{nd}$ moment), the skewness ($3^{rd}$ moment), and the kurtosis($4^{th}$ moment). Definitions of those descriptive statistics can be found in many publications (e.g., [28]) and thus will not be provided here.

These descriptive statistics can be calculated directly on raw signals. However, for the descriptive statistics to be more effective in bearing condition monitoring, they are frequently calculated on

filtered or processed signals.  In [28], the descriptive statistics of vibration signals were calculated for two different frequency bands. Realizing signal differences and sum (integrals) are equivalent to low-pass and high-pass filtering, respectively, [6][5] calculated the statistics on the derivatives and integrals of the signals.

**b) Model-based approaches:** Model-based feature extraction involves treating vibration signals as time series data and fitting them to a parametric time series model. The model parameters are then used as features.  The most popular time series model used for bearing diagnosis is the autoregressive (AR) model. Poyhonen et al. [27] applied AR model to vibration signals collected from an induction motor and use the AR model coefficients as extracted features. Other time-series models, such as the autoregressive moving average (ARMA) and other nonlinear models, such as neural networks and support vector machines, can also be used.

Baillie and Mathew [8] compared three different autoregressive models, namely linear autoregressive models, back-propagation neural networks, and radial basis function networks, even though they used the three models for model-based bearing fault diagnosis, not explicitly feature extraction purpose.

Recent direction for model-based feature extraction seems on extending model-based approaches that work for stationary signals to non-stationary signals. For example, Chen et al [26] used empirical mode decomposition (EMD) to decompose the non-stationary signals into a number of intrinsic mode function (IMF) components that are stationary. An AR model was then applied to each of the IMF components.

**c) Time-domain DSP approaches:** Classical digital signal processing includes filtering, averaging, correlation, and convolution. Another popular DSP technique is Synchronous averaging [10]. More recently, several techniques rooted in chaos theory have been adapted to feature extraction. For example, fractal dimension [1][2], correlation dimension [14][15].

**3.1.2. Frequency domain techniques:** Time-domain features are generally considered to be good for fault detection, but less effective for fault isolation, i.e., to determine where the defect is located, inner race, outer race, rolling elements, and cage. For fault isolation, frequency-domain features are generally more effective. Frequency-domain feature extraction methods include spectral analysis, envelope analysis, cepstrum, and higher-order spectra.

**a) Spectral Analysis:** The most popularly used method is the spectral analysis. A spectrum (more practically power spectrum) obtained from fast Fourier transform (FFT) of a vibration signal represents frequency characteristics of the signal. Either the entire spectrum or the frequency amplitudes at the bearing characteristic frequencies calculated from the power spectrum of vibration signals can be used as features.

In Li's work [3], to consider the energy leakage (spreading over a wide frequency band), features were calculated as the sum of the amplitudes over a frequency band of 5Hz centered at the defect frequencies. Instead of a fixed bandwidth, Saleh et al (2003) further proposed variable bands where bandwidths are determined as a percentage of the interested frequencies. The features at the interested frequencies were then calculated either as the average value of the banded components, or the maximum value of the banded components, or the energy within the frequency bands.

Descriptive statistics of spectra can also be used as features. For example, Wu and Chow (2004) [4] extracted the total power, average frequency, and dispersion indices (2nd and 3rd central moments) of the power spectra of vibration signals.

Raw spectra for bearing vibration signals may not be appropriate for directly calculating features. Smoothing raw spectra may be necessary before calculating features. Power spectral density (PSD) is considered to be one of the spectra smoothing techniques.

**b) Envelope analysis:** Envelope analysis, also known as amplitude demodulation or high frequency resonance technique (HFRT) [47], is another widely used frequency domain technique for bearing fault diagnosis. Envelope analysis consists of two steps: band-pass filtering and enveloping. During bearing operation, wide band impulses are generated when rolling elements pass over the defect. Certain vibration modes of the bearing and its supporting structure will be excited by the periodic impulses. Band-pass filtering allows keeping only signal components around the resonance frequency. Enveloping is then to remove the structural resonance and preserve the defect impact frequency. Thus envelope analysis can be used for detecting incipient faults of bearings. The key for envelope analysis to be effective is intelligently selecting frequency band.

**c) Cepstral analysis:** Cepstrum, defined as the power spectrum of the logarithm of the power spectrum of the signal, is used for detecting the periodicity of spectra. A defect in a bearing element (ball and races) generates impulses and the bearing and its structure respond to the impulses. Bearing vibration signals thus are the result of convolution between impulses and the system's response to these impulses, which leads to harmonic series in the spectra. Cepstral analysis is to detect common spacing between the harmonics. Cepstrum analysis has been used for bearing fault detection and diagnosis, e.g., [48].

**d) Higher order spectra:** Higher order spectra typically refer to bispectrum and trispectrum. Higher order spectra are also called higher order statistics since bisprctrum and trispectrum are essentially the Fourier transform of the 3rd- and 4th-order statistics of signals. Higher order spectra (i.e., bispectrum or trispectrum) have proved to have more diagnostic information. Advantages for using higher order spectra include additive Gaussian noise suppression, non-minimum phase system identification, nonlinear systems detection and identification [49]. Li et al [36] presented bicoherence signal analysis for detection of faults in bearings. The rationale behind the bicoherence analysis is that interactive coupling between various frequencies and existing bearing fault frequencies can be amplified and detected by monitoring the statistical dependence or correlations between the energies in the corresponding frequency-combinations.

**3.2. Non-stationary signals:** For non-stationary signals, since the statistical properties change over time, traditional spectral analysis becomes ineffective. Techniques used for tackling non-stationary signals include time-frequency techniques and wavelet analysis, which are detailed as follows.

**3.2.1. Time-frequency analysis techniques:** Time-frequency analysis techniques analyze signals in both time and frequency simultaneously for identifying time-dependent variations of frequency components within the signal, which makes time-frequency analysis techniques a powerful tool for analyzing non-stationary signals. The most commonly used time-frequency analysis techniques are the short-time Fourier transform (STFT), the Wigner-Ville distribution, and the wavelet transform. In this paper we categorize wavelets as a separate group due to its popularity and various types. Other newly developed time-frequency analysis techniques include spectral kurtosis, empirical mode decomposition, and cyclostationary analysis.

**a) Short-time Fourier transform (STFT):** STFT tackles non-stationary signals by applying the conventional FFT to a sliding window of the signal, which can be assumed to be locally stationary. The squared magnitude of the STFT, often referred as the spectrogram, provides the energy density spectrum of the signal as a function of time. Time resolution is determined by segment length. Thus the success of STFT is hinged on properly choosing window length, which often time is difficult. Using STFT for bearing monitoring and diagnosis have shown in many publications, for example, [22].

**b) Wigner–Ville distribution:** The afore-mentioned STFT is conceptually simple. However, this simple scheme has a severe drawback, that is, it cannot provide good resolution simultaneously in both time and frequency domains. Wigner-Ville distribution [50] is a bilinear transform, thus does not have the limitation of the spectrogram. However, bilinear transform gives the interference terms that make interpretation of the estimated distribution difficult. The Choi-Williams time-frequency distribution [51] was developed to overcome this disadvantage.

**c) Spectral kurtosis:** Spectral kurtosis (SK) was first introduced as statistical tool for detecting the presence of transients (non-stationary components) in a signal and their location in the frequency domain. Antoni and Randall [29] proposed a comprehensive formalization and introduced it into rotating machine diagnostics. They observed that SK and power spectral density (PSD) are supplementary each other: PSD can be thought of a measure of position (time-average), whereas the SK as a measure of dispersion (time variance) of a time-frequency energy density [30]. Be definition, SK is large in frequency bands where the impulsive bearing fault signal is dominant and essentially zeros in the bands where stationary components are dominant. SK has often been used for selecting frequency bands for demodulation and filtering [31]. To use SK for feature extraction, one can simply follow what we did in spectral analysis for feature extraction, that is, calculating kurtosis at bearing characteristic frequencies. Other characteristics, such as maximum value, mean value, and even shape statistics, can also be calculated and used as features.

**d) Empirical mode decomposition:** Proposed by Huang et al [35], empirical mode decomposition (EMD) is a new time-frequency domain signal analysis method. EMD decomposes a complicated signal into a finite number of intrinsic mode functions (IMFs). Each of those IMFs can then be analyzed to extract characteristic information of the original signal. In [16], so-called EMD energy entropy calculated from each of the IMFs were used as features for roller bearing fault diagnosis. They even showed that EMD-based features could identify roller bearing fault patterns more effectively than those based on wavelet packet decomposition do. In [17], the non-stationary vibration signal of a roller bearing was first decomposed by EMD into IMFs that were stationary. An AR model was established for each IMF and the AR parameters were used as features for bearing fault diagnosis.

**e) Cyclostationary analysis:** Realizing that rolling-element bearing vibrations are cyclostationary, [32] [33] introduced cyclostationary analysis (CA) to bearing vibration analysis as an alternative framework to other time-frequency analysis methods. The center part of CA is its spectral correlation function (also called cyclic spectral density (CSD)), which is obtained by performing 2D Fourier transform of the autocorrelation function of the vibration signal with respect to two time variables. CSD indicates how spectral content evolves periodically in time, thus can be a powerful tool for distinguishing different types of signals (stationary, nonstationary, and periodic) and can be used for identifying the source of faults [31]. It has been proved in [34] that integration of cyclic spectral density over all frequencies is equivalent to Fourier transform of the mean squared signal, thus linked the integrated CSD to envelope analysis.

**f) Adaptive signal processing techniques:** The goal of an adaptive representation algorithm is to find an approximation of a signal, in terms of a given over-complete dictionary of waveforms, that optimizes a desired characteristic. A number of methods for obtaining signal representations in over-complete dictionaries have been developed in recent years, for example, the matching pursuit [51] and the basis pursuit [19][20].

**3.2.2. Wavelet Analysis techniques:** Wavelets can be used to perform multiresolution analysis of the bearing vibration signal, which involves application of a cascade of adjacent band-pass filters to the signal. This ability is useful in assessing the signal content at varying frequencies. For the primary problem of detection, an increase in the energy of the high frequency signal can often indicate the presence incipient faults due to early spalls as well as lubrication problems.

Multiresolution analysis is also useful for detecting the presence of bearing defect frequencies. Bearing defect frequencies result from the periodic impacts of the defective component; these impacts can transfer energy across a wide band of resonance frequencies. Since multiresolution analysis using wavelets preserves time information as well, all of the time-domain techniques and features can be applied to the signal constructed at an appropriate resolution.

Features based on wavelets include values of wavelet coefficients, resolution-specific energy content. The ability to decompose a signal into components at varying frequencies also has the advantage for discriminating multiple types of faults since the contribution of each fault can often be different at different frequencies. Use of wavelet transform to extract defect features from vibration signals have been examined by various early works in literature, Cheung et al [45], Mori et al [42], Li et al [36], Yang et al [43], and Staszewski et al [44], to name a few. Peng and Chu [24] conducted a review on application of wavelet transform in machine condition monitoring and fault diagnostics. More recent works focus on the use of wavelets that are customized to either the bearing signature or to localize analyses on a resonant band with highest sensitivity, as well as from the supervised learning perspective, as in the embedding of wavelets into neural networks.

Wavelets are also useful for transient analysis of signals and therefore for detection of faults that are amplified by analysis of transient vibration signals Wang and McFadden [37] and Wang [38] presented techniques for use of time-frequency representation in the analysis of transient vibration signals. Sahambi et al [40] presented the use of wavelets to characterize electrocardiograms (ECG) for online detection of relevant timing intervals in the ECG events that can be used for better interpretation of ECG signals. Holm-Hansen et al [41] presented the use of the actual impulse response of a ball bearing to construct a customized wavelet analytically and use it for the detection of defects in the bearing. The customized wavelet approach is shown to provide better sensitivity in the detection of bearing induced signatures compared to other standard mother wavelets for the same analysis.

Shi et al [39] presented a wavelet-based technique to improve the sensitivity of the traditional enveloping. The make use of Shannon Entropy of wavelet-based spectra to identify the optimal scale and thus optimal resonance frequency to monitor bearing condition.

Wavelet neural networks (WNNs) [46] provide a mechanism to avoid explicit extraction of features from the wavelet transforms. Rather, it is a technique by which the informative features can be tuned under the adaptive learning capabilities of classical neural networks to tune the parameters of the mother wavelet to best separate normal signals from known faulty-containing signals.

8

Several types of features can be extracted from wavelet-based methods, which can be categorized roughly into wavelet coefficient-based, wavelet energy-based, singularity-based, and wavelet function-based methods [21].

**3.3. Other techniques:** In addition to afore-mentioned feature extraction techniques, there are other methods that utilize computation intelligence techniques for constructing features, for example, in [6] [7], genetic programming (GP) was used to construct better features. Other statistical transformation methods, such as principal component analysis (PCA) and linear discriminant analysis (LDA), can also be used for constructing higher-level features out of the original features.

**4. Conclusions:** Identifying a set of salient signatures/features has always been an important and challenging task in multiple fields, such as, machine learning, pattern recognition, and data-mining. Extracting good features from sensor measurements is also critical in design of bearing PHM systems. With increasing demand for more advanced bearing PHM technologies and continuously increasing research attention to feature extraction technologies, a large number of feature extraction techniques have been explored. This paper attempts to survey some of those feature extraction techniques, especially the recent developments. Even though our survey is not meant to be exhaustive, we hope that this work will be helpful to those who are interested in feature extraction in general and to those who are involved in choosing proper feature extraction methods for their own applications.

**REFERENCES:**

1. Nelwamondo, F.V., Marwala, T., and Mahola, U. (2006), "Early classifications of bearing faults using Hidden Markov models, Gaussian mixture models, Mel-frequency cepstral coefficients and fractals", International Journal of Innovative Computing, Information and Control, 2(6), pp1281-1299
2. Yang, J., Zhang, Y., and Zhu, Y., "Intelligent fault diagnosis of rolling element bearing based on SVMs and fractal dimension", Mechanical Systems and Signal Processing, 21, pp2012-24, 2007
3. Li, B., Chow, M.Y., Tipsuwan, Y., and Hung, J.C., "Neural-network-based motor rolling bearing fault diagnosis", IEEE Transactions on Industrial Electronics, 47(5), pp 1060-1069, October, 2000.
4. Wu, S. and Chow, T., "Induction machine fault detection using SOM-based RBF neural networks", IEEE Transactions on Industrial Electronics, 51(1), pp183-194, Feb. 2004.
5. Samanta, B., Al-Balushi, K.R., and Al-Araimi, S.A., "Artificial neural networks and support vector machines with genetic algorithm for bearing fault detection", Engineering Applications of Artificial Intelligence, 16 (2003), pp657-665.
6. Zhang, L., Jack, L.B., Nandi, A.K., "Fault detection using genetic programming", Mechanical Systems and Signal Processing, 19(2005), pp271-289.
7. Guo, H., Jack, L.B., and Nandi, A.K., "Feature generation using genetic programming with application to fault classification", IEEE Transactions on Systems, Man, and Cybernetics – Part B, 35(1), 2005, pp89-99.
8. Baillie, D.C. and Mathew, J., "A comparison of autoregressive modeling techniques for fault diagnosis of rolling element bearings", Mechanical Systems and Signal Processing 10 (1996), pp1–17.
9. Lei, Y., He, Z., Zi, Y., and Chen, X., "New clustering algorithm-based fault diagnosis using compensation distance evaluation technique", Mechanical Systems and Signal Processing, 22(2), February 2008, pp 419-435
10. McFadden, P.D. and Toozhy, M.M., "Application of synchronous averaging to vibration monitoring of rolling element bearing", Mechanical System and Signal Processing 14 (6) (2000), pp891–906.

11. Jardine, A.K.S., Lin, D., and Banjevic, D., "A review on machinery diagnostics and prognostics implementing condition-based maintenance", Mechanical Systems and Signal Processing, 20 (2006), pp1483-1510.

12. Zhou, W., Habetler, T.G., and Harley, R.G., "Bearing condition monitoring methods for electric machines: A general review", Proceedings on IEEE International Symposium on Diagnostics for Electric Machine, Power Electronics and Drivers (SDEMPED 07), Sept. 6 – 8, 2007, Cracow, Poland, pp3-6.

13. Baillie, D.C. and Mathew, J., "A comparison of autoregressive modeling techniques for fault diagnosis of rolling element bearings", Mechanical Systems and Signal Processing, 10(1), 1996, pp1-17.

14. Logan, D. and Mathew, J., "Using the correlation dimension for vibration fault diagnosis of rolling element bearings – I: Basic concepts", Mechanical Systems and Signal Processing, 10(3), pp241-250, 1996.

15. Logan, D. and Mathew, J., "Using the correlation dimension for vibration fault diagnosis of rolling element bearings – II: Selection of experimental parameters", Mechanical Systems and Signal Processing, 10(3), pp251-264, 1996.

16. Yang, Y., Yu, D., and Cheng, J., "A roller bearing fault diagnosis method based on EMD energy entropy and ANN", Journal of Sound and Vibration, 294, 2006, pp269-277.

17. Cheng, J., Yu, D., and Yang Y., "A fault diagnosis approach for roller bearings based on EMD method and AR model", Mechanical Systems and Signal Processing, 20, 2006, pp350-362.

18. Gao, Q., Duan, C., Fan, H., and Meng, Q., "Rotating machine fault diagnosis using empirical mode decomposition", Mechanical Systems and Signal Processing, 2007, article in press.

19. Yang, H., Mathew, J., and Ma, L., "Basis pursuit-based intelligent diagnosis of bearing faults", J. of Quality in Maintenance Engineering, 13(2), 2007, pp152-162

20. Yang, H., Mathew, J., and Ma, L., "Fault diagnosis of rolling element bearings using basis pursuit", Mechanical Systems and Signal Processing, 19, 2005, pp341-356

21. Vachtsevanos, G., Lewis, F.L., Roemer, M., Hess, A., and Wu, B., "Intelligent fault diagnosis and prognosis for engineering systems", John Wiley & Sons, Inc., Hoboken, New Jersey, pp124-125.

22. Gao, R.X. and Yan, R., "Non-stationary signal processing for bearing health monitoring", International J. Manufacturing Research, Vol. 1, No. 1, pp.18–40, 2006.

23. Li, J.C. and Ma, J., "Wavelet decomposition of vibrations for detection of bearing-localized defects", NDT&E International, Vol. 30, No.3, pp143-149, 1997.

24. Peng, Z.K. and Chu, F.L., "Application of the wavelet transform in machine condition monitoring and fault diagnostics: a review with bibliography", Mechanical Systems and Signal Processing, 18, 2004, pp199-221.

25. Jardine, A.K.S., Lin, D., and Banjevic, D., "A review on machinery diagnostics and prognostics implementing condition-based maintenance", Mechanical Systems and Signal Processing, 20,2006, pp1483-1510.

26. Chen, J., Yu, D., and Yang, Y., "A fault diagnosis approach for roller bearings based on EMD method and AR model", Mechanical Systems and Signal Processing, 20, 2006, pp350-362.

27. Poyhonen, S., Jover, P., and Hyotyniemi, H., Signal processing of vibrations for condition monitoring of an induction motor, in: ISCCSP: 2004 First International Symposium on Control, Communications and Signal Processing, New York, 2004, pp. 499–502.

28. Sun, Q., Chen, P., Zhang, D., and Xi, F., "Pattern recognition for automatic machinery fault diagnosis", Journal of Vibration and Acoustics, Vol. 126, April 2004, pp307-316.

29. Antoni, J. and Randall, R.B., "The spectral kurtosis: application to the vibratory surveillance and diagnostics of rotating machines", Mechanical Systems and Signal Processing, 20 (2), 2006, pp308-331.

30. Antoni, J., "The spectral kurtosis: a useful tool for characterizing non-stationary signals", Mechanical Systems and Signal Processing, 20 (2), 2006, pp282-307.

31. Sawalhi, N., "Diagnostics, prognostics and fault simulation for rolling element bearings", PhD Dissertation, School of Mechanical and Manufacturing Engineering, University of New South Wales, Australia, April 2007.

32. McCormick, A.C. and Nandi, A.K., "Cyclostationary in rotating machine vibrations", Mechanical Systems and Signal Processing, 12(2), 1998, pp225-242.

33. Antoniadis, I. and Glossiotis, G., "Cyclostationary analysis of rolling element bearing vibration signals", Journal of Sound and Vibration, 248(5), 2001, pp829-845.

34. Randall, R.B., Antoni, J., and Shobsaard, S., "The relationship between spectral correlation and envelope analysis in the diagnostics of bearing faults and other cyclostationary machine signals", Mechanical Systems and Signal Processing, 15(5), 2001, pp945-962.

35. N.E. Huang, Z. Shen, S.R. Long, "A new view of nonlinear water waves: the Hilbert spectrum", Annual Reviews of Fluid Mechanics, 3 (1999), pp 417–457.

36. C. James Li, J. Ma, B. Hwang, "Bearing Localized Defect Detection by Bicoherence Analysis of Vibrations," Journal of Engineering for Industry, Transactions of ASME, Vol. 117, Nov.1995, pp 626-629.

37. Wang W.-I., and McFadden, P.D., 1996, "Application of Wavelets to Gearbox Vibration Signals for Fault Detection," J. Sound Vib., 192(5), pp. 927-939.

38. Wang, W. J., 2001, "Wavelets for Detecting Mechanical Faults With High Sensitivity," Mech. Syst. Signal Process, 15(4), pp. 685-696.

39. Shi D. F., Wang W. J., Qu L. S., "Defect Detection for Bearings Using Envelope Spectra of Wavelet Transform", Journal of Vibration and Acoustics, Oct 2004, vol. 126, pp. 567-573.

40. Sahambi, J. S., Tandon, S. N., Bhatt, R.K.P., "Using Wavelet Transforms for ECG Characterization," IEEE Engineering in Medicine and Biology, Jan 1997, pp. 77-83.

41. Holm-Hansen, B. T., Gao R. T., Zhang L., "Customized Wavelet for Bearing Defect Detection", Transactions of the ASME, vol. 126, Dec 2004, pp. 740-745

42. Mori K., Kasashima N., Yoshioka T., and Ueno, Y., 1996, "Prediction of Spalling on a Ball Bearing by Applying the Discrete Wavelet Transform to Vibration signals," Wear, 195(1-2), pp. 162-168.

43. Yang, J., Xiong X., and Xiong, S., 1999, "Damage Detection of Roller Bearing using Wavelet Transforms," Proc. Of Int. Modal Analysis Conference-IMAC, vol. 2, Society for Experimental Mechanics, Bethel, CT, pp. 1980-1983.

44. Staszewski, W., Ruotolo, R. and Storer, D., "Fault Detection in Ball Bearings Using Wavelet Variance," IMAC Proc. Of 1999 17th Int. Modal Analysis Conference, Vol. 2, Society for Experimental Mechanics, Bethel, CT, pp. 1335-1339

45. Cheung, C., Chui, C., and Chan, A., 1993, "Real-time detection of transient signals using Spline-Wavelets," Proceedings-ICASSP, IEEE Int. Conference on Acoustics, Speech and Signal Processing, Vol. 4, pp. 361-364.

46. Zhang, Q. and Benveniste, A., "Wavelet Networks," IEEE Transactions on Neural Networks, Vol. 3, No. 6, pp. 889-898.

47. McFadden, P.D. and Smith, J.D., "Vibration monitoring of rolling element bearings by the high frequency resonance technique – a review", Tribology International, 17, 1984, pp3-10.

48. Zheng, G.T. and Wang, W.J., "A new cepstral analysis procedure of recovering excitations for transient components of vibration of signals and applications to rotating machinery condition monitoring", Journal of Vibration and Acoustics, Vol. 123, April 2001, pp222-229.

49. Arthur, N. and Penman, J., "Induction machine condition monitoring with higher order spectra", IEEE Transactions on Industrial Electronics, 47(5), Oct. 2000, pp1031-1041.

50. Cohen, L., Time–Frequency Analysis, Prentice-Hall, Englewood Cliffs, NJ (1995).

51. Liu, B., Ling, S.F. and Gribonval, R., "Bearing failure detection using matching pursuit", NDT & E International, Vol. 35 No. 4, 2002, pp. 255-62.

52. Gustaffson, O.G. and Tallian, T., "Detection of damage of assembled rolling bearings", ASME Transactions, 5 (1962), pp197–209.

53. McFadden, P.D. and Smith, J.D., "Model for the vibration produced by a signal point defect in a rolling element bearing", Journal of Sound and Vibration, 96 (1), 1984, pp69–82.

54. Ho, D. and Randall, R.B., "Optimization of bearing diagnostic techniques using simulated and actual bearing fault signals", Mechanical Systems and Signal Processing, 14 (5), 2000, pp763–788.

55. Harris, Tedric A., *Rolling Bearing Analysis*, John Wiley, 2001.

56. Johannes Brändlein, Paul Eschmann, Ludwig Hasbargen, Karl Weigand, *Ball and Roller Bearings: Theory, Design and Application*, Wiley, 1999.