# Review of Automatic Fault Diagnosis Systems Using Audio and Vibration Signals

Patricia Henríquez, Jesús B. Alonso, Miguel A. Ferrer, and Carlos M. Travieso

*Abstract*—The objective of this paper is to provide a review of recent advances in automatic vibration- and audio-based fault diagnosis in machinery using condition monitoring strategies. It presents the most valuable techniques and results in this field and highlights the most profitable directions of research to present. Automatic fault diagnosis systems provide greater security in surveillance of strategic infrastructures, such as electrical substations and industrial scenarios, reduce downtime of machines, decrease maintenance costs, and avoid accidents which may have devastating consequences. Automatic fault diagnosis systems include signal acquisition, signal processing, decision support, and fault diagnosis. The paper includes a comprehensive bibliography of more than 100 selected references which can be used by researchers working in this field.

*Index Terms*—Condition monitoring, fault diagnosis, maintenance.

## I. INTRODUCTION

CONDITION monitoring (CM) and its role in fault diagnosis of machinery have recently attracted researchers because of CM's great influence on the operational continuity of many industrial processes. An unexpected failure can result in a devastating accident and in financial losses for the company. Early detection prevents failures from growing and eventually turning into serious problems. Consequently, CM of industrial scenarios helps to reduce maintenance costs and increase the machinery lifetime. The advantages of a monitoring system and their expected percentages of improvement are shown in Table I [1]. Implementation of CM systems adds extra costs due to sensors, circuits, and control systems. Computational effort is also required for data processing and decision-making, and memory storage is necessary for knowledge databases. The increase in costs for these measures is later compensated by increases in security and reliability.

Earlier maintenance techniques include over-current protection relays or ground failure protection, while the latest

TABLE I
IMPROVEMENTS IN RELIABILITY USING A MONITORING SYSTEM [1]

| | |
|---|---|
| Maintenance costs | Reduction of 50%–80% |
| Equipment damages | Reduction of 50%–60% |
| Extra hours expenses | Reduction of 20%–50% |
| Machine life expectancy | Increase of 50%–60% |
| Total productivity | Increase of 20% to 30% |

developments introduce signal processing techniques together with artificial intelligence. Maintenance techniques can be divided into corrective maintenance and preventive maintenance (PM). In corrective maintenance, actions are carried out after a fault has occurred. These actions lead to fixing the fault or to postponing the repair.

PM was introduced in the 1950s and can be divided into predetermined preventive maintenance (pdPM) and condition-based maintenance (CBM). In pdPM, scheduled maintenance activities are performed in periodical intervals to prevent components from degrading. The machine is repaired or a part is changed before the fault occurs. Corrective and pdPM approaches have shown to be costly in many applications for several reasons (e.g., lost production, cost of keeping spare parts, and quality deficiencies). For this reason, some industries started performing CBM in the 1980s. CBM refers to machine CM in which information is continuously collected on parameters that indicate the condition of a machine. The parameters' deviation from the normal condition indicates the development of a failure. CBM takes maintenance action only when there is evidence of abnormal behavior. For this reason, CBM reduces the number of scheduled PM activities [3]. A CM system usually includes four stages: 1) Data acquisition: collection of relevant information about the machine condition (i.e., the machine's signature); 2) Signal processing; 3) Decision Support System: classification of the previously analyzed data into different condition states; and 4) Fault diagnosis/prediction: fault diagnosis comprises the detection and identification of faults and fault prediction estimates the remaining time for a fault to occur.

This paper focuses on the review of vibration- and audio-based fault diagnosis. Due to the complexity of vibration and audio signals in fault diagnosis, mathematical transformations, signal processing, and pattern recognition techniques are widely used to extract useful features from these signals to discriminate between different machine conditions, and to follow the machine degradation process. Vibration-based
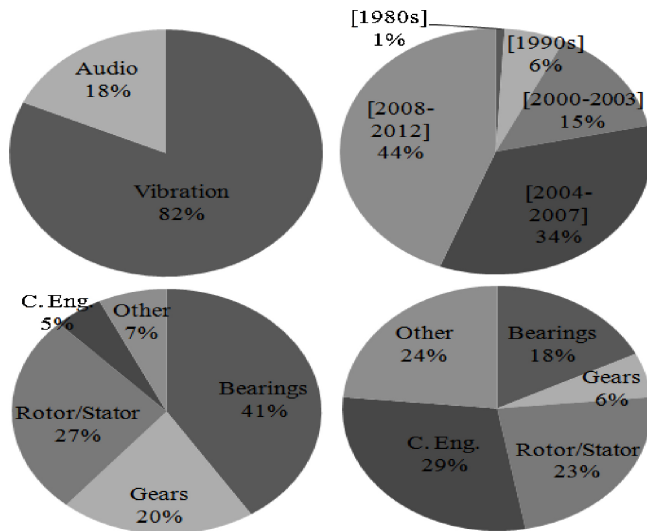
Fig. 1. Distributions of referenced papers. Upper left: audio and vibration-based fault diagnosis distribution. Upper right: publishing years distribution. Bottom left: distribution of faults in vibration-based diagnosis. Bottom right: distribution of faults in audio-based diagnosis.

fault diagnosis is a well-established field that includes a wide range of techniques which have rapidly evolved during the last decades. Audio-based fault diagnosis using microphones is an emerging field with a great potential in fault diagnosis since microphones are noninvasive sensors. Some previous reviews to 2006 using different kinds of machine signatures are available in the literature [2]–[5], and some works are focused only on vibration-based fault diagnosis [6]–[8]. However, the authors have not found previous reviews which focus on audio-based fault diagnosis using microphones. This paper addresses this subject and highlights the current and most valuable lines of research on audio and vibration-based techniques which we have identified in the period from six years ago until now. The most referenced papers belong to vibration-based diagnosis and were published from 2004 to 2012 (Fig. 1). Several kinds of faults can be detected using vibration and audio signals. Fig. 1 shows the fault distribution of the referenced papers when vibration- and audio-based fault diagnosis are used. In the case of vibration-based papers, most references are related to bearing faults, followed by rotor/stator faults and gears. In the case of audio-based papers, most references are related to combustion engine faults. Most of these faults occur in motors, pumps, fans, helicopters, end-milling machines, on load tap chargers (OLTC) of power transformers and in bearing, gear, and rotor test-rigs.

The remainder of this paper is divided into five sections. Sections II–IV focus on the steps of a CM system (acquisition, data processing, and decision stage). Section V reports on some examples of CM systems. The last section is devoted to a discussion and conclusion.

## II. ACQUISITION

Good quality and precision of the signal in the acquisition stage is essential for posterior analysis and feature extraction.

In this paper, we focus on vibration and audio signals acquired by accelerometers and microphones, respectively.

The dynamic forces within a machine produce compression and bending waves. This vibration pattern changes when an incipient failure starts to evolve. Thus, the analysis of vibration signals is a useful tool for establishing the machine's condition. To detect these signals, vibration sensors are mounted directly onto the machine. There are different kinds of sensors depending on the frequency range: position sensors (0 Hz–10 kHz), velocity sensors (10 Hz–1 kHz), and accelerometers (8 Hz–15 kHz). Piezoelectric accelerometers are popular because of their higher dynamic range of frequencies, reliability, robustness, and smaller dimensions. The number and location of vibration sensors is an important issue discussed in [7].

The acoustic characteristics of a machine change when a fault evolves. Consequently, the sound of a machine carries information about its condition. Extracting the sound signature of the machine is a useful tool in fault diagnosis [1]. We focus our review on audio signals obtained with microphones. They usually acquire sounds in the 0 Hz–20 kHz range. Some microphones can even acquire signals above 100 kHz. Microphones are not mounted directly onto the machine. As a result, they are less intrusive than vibration sensors, but they are more sensitive to environmental noise. For this reason, microphones must be pointed to the machine or system under consideration and should be placed from 2 to 10 cm from the wanted source [1], [11].

## III. PROCESSING STAGE

Signal processing transforms original signals into useful features to accomplish fault diagnosis. These features should be independent of the normal machine operating conditions (variations of load and speed) and extraneous noise and be sensitive only to machinery faults. This section is divided into vibration and audio signals analysis. Table II shows some of the most common vibration and audio features discussed in the literature and their evolution in time.

### A. Vibration Signal Processing

The main processing techniques applied to vibration signals are based on time analysis, frequency and cepstral analysis, time-frequency analysis, and nonlinear analysis.

1) *Time Domain Analysis:* Signal processing in the time domain extracts information from the vibration signal as a function of time. Conventional techniques include several time features, such as root mean square, crest factor [34], variance, skewness, kurtosis, and higher-order moments [67], [92]. Some features, such as crest factor, kurtosis, impulse, and clearance factors, do not vary with load and speed variations and are good indicators for impulsive faults [34], [59], [67] especially in bearings. Other conventional techniques are time-averaging methods, including time synchronous average (TSA), residual signal, and difference signal, all of which are powerful tools in the detection of gear faults [35], [36], [101]. TSA removes background noise and periodic events that are not synchronous with the gear of interest. The resulting signal

TABLE II
VIBRATION AND AUDIO FEATURES

| Methods | | Evolution | | | |
|---|---|---|---|---|---|
| | | 1980–1999 | 2000–2003 | 2004–2007 | 2008–2012 |
| Time | Statistics | — | — | [58] (A) | [36] (V) |
| | TSA | — | — | — | [35] (V) |
| | AR, ARMA models | — | [29] (V) | [37] (V) | [101] (V) |
| Frequency | Statistics | — | — | [55], [57], [58] (A) | [51] (A); [34], [53], [62], [66] (V) |
| | EnA (HT) | [15] (V) | [25] (A) | — | [62], [76] (V) |
| | SIW | — | — | — | [102] (V) |
| | TEO | — | — | [99] (V) | [49] (V) |
| | Cyclostationarity | — | [83] (V) | — | [97] (V) |
| | Polyspectrum (HOS) | — | [16], [17] (V) | [38] (V) | |
| Cepstral | Cepstrum | [82] (V) | — | [18] (V) | — |
| | MFCC | — | — | [39] (V) | [53] (A) |
| Time-Frequency | STFT, WVD, Choi dist. | — | [40], [41] (V) | [55] (A) | [53], [85] (A) |
| | WT (CWT, DWT, WPT) | — | [11] (V, A) | [12], [19], [38] (V) | [35], [46]; [56] (A) |
| | SGWT (IWPT) | — | — | [43] (V) | [67] (V) |
| | RSGWT | — | — | — | [107] (V) |
| | dtcWT | — | — | — | [93] (V) |
| | Generalized S transform | — | — | — | [106] (V) |
| | MuSEnS | — | — | — | [45] (V) |
| | EMD, HHT, EEMD | — | — | [20] (V) | [34], [42] (V) |
| | ItHT | — | — | — | [105] (V) |
| | LMD | — | — | — | [109] (V) |
| | GDTF | — | — | — | [98] (V) |
| | SK | — | — | — | [103], [104] (V) |
| Nonlinear | Phase portrait, dot pattern | — | [9] (A), [10] (V) | — | — |
| | CD, fractals | [21] (V) | [17], [22] (V) | [23], [51] (V), [54] (A, V), [24] (A) | [50], [94] (V) |
| | ApEn | — | — | [47], [48] (V) | — |
| | Lyapunov exponents | [13] (V) | — | — | — |
| | Multiple manifold | — | — | — | [108] (V) |

V, vibration; A, audio.

is used for posterior advanced analysis [79]. Autoregressive (AR) modeling [29] and AR moving average (ARMA) modeling [37] have also proved to be efficient tools in modeling transients in the vibration signal. Novel approaches include a modification of the time-varying AR and ARMA models in which the coefficients are updated with the incoming vibration signal [36]. These models are robust to variations in load and speed. Another novel AR approach [101] proposes the load information as an exogenous input.

*2) Frequency and Cepstral Domain Analysis:* Frequency analysis gives information about the periodicity of the signal in the peaks of the frequency and detects harmonics and sidebands. Conventional frequency features, such as the mean and standard deviation of the frequency, the root mean square frequency, peak magnitude, energies, and ratios of spectral energies, are used in fault diagnosis in pumps, motors, and gearboxes [34], [62], [66]. Another conventional technique is envelope analysis (EnA) or the amplitude demodulation technique, used especially in bearings [6], [15], [62] to identify the bearing defect characteristic frequency and also in gears [75]. EnA improves the signal-to-noise ratio (SNR) and makes the spectral analysis more effective. For a good review of EnA see [15]. EnA is usually applied using the Hilbert transform (HT) [15]. Recently, the skewness information wave (SIW) has been proposed to compute EnA without using the HT [102]. The skewness is computed in small regions of the

signal, resulting in a skewness wave. The SIW is obtained using the Kullback–Libeller divergence information from the skewness wave of the reference signal (measured far from the diagnostic location) and the diagnosis signal (measured in the diagnostic location). Then the envelope SIW is obtained from their absolute values and the spectrum is computed. This method is shown to be superior to the conventional EnA and more robust to strong background noise. Another novel EnA method is the Teager energy operator (TEO) [49], [99]. TEO is a nonlinear operator with higher demodulation precision and needs less calculation than HT.

Cepstral analysis, which gives information from the vibration signal as a function of quefrency has, since the 1990s, been shown to be effective in fault diagnosis [82]. Power cepstrum gives information about the periodicity of the spectrum and detects harmonics and sideband patterns in the power spectrum. The application of Mel-frequency cepstral coefficients (MFCC), a technique from speech processing to vibration fault diagnosis [39] was proposed in 2006. MFCC contain both time and frequency information of the signal which makes them more useful for feature extraction in vibration signals. In 2007, a method called minimum variance cepstrum was proposed to detect faulty periodic impulses in bearings in noisy environments [18]. It minimizes the variance of the signal power in its cepstrum representation.

Another family of techniques is based on higher-order statistics (HOS) in the frequency domain; bispectrum, summed bispectrum, and bicoherence have, since the late-1990s, been shown to be effective in fault diagnosis in the bearings of induction motors, gearboxes, and in flexible rotor systems [16], [17], [38]. These provide more information than the power spectra, in the case of non-Gaussian signals, can detect nonlinear couplings and can explain the origin of certain peaks in the power spectra. For instance, [95] proposed in 2009 the use of HOS in the cepstral domain (bicepstrum) to detect failures in gears. This technique eliminated noise and modulation effects caused in gears.

Conventional frequency techniques assume stationarity and linearity, and are usually applied in machines working at fixed speeds. However, most machine processes presents nonstationary components in speed-up, speed-down, and in several faults. Cyclostationary analysis (a second-order technique in the frequency domain), and time–frequency techniques are more appropriate for nonstationary processes. The periodic variation of statistical moments of rotating machinery makes cyclostationarity techniques suitable for early fault detection [83], [97].

*3) Time–Frequency Domain Analysis:* Time–frequency analysis extracts information from the vibration signal as a function of time and frequency and overcomes the problems encountered in frequency analysis when analyzing nonstationary events. Some conventional time–frequency techniques include short-time Fourier transform (STFT) [40], Wigner–Ville distribution (WVD) [40], [55], and the directional Choi–Williams distribution [41]. Techniques from the late 1990s include empirical mode decomposition (EMD) [34], [42], the Hilbert–Huang transform (HHT) [20], [34], and the wavelet transform (WT) [11], [80]. The WT has adjustable window size through the choice of the mother wavelet and different approximation scales. This flexibility makes it suitable for the analysis of nonstationary signals. Multiple features, such as singularity points [19], Lipschitz exponents [12], scalogram [35], energies, statistics, and entropies [43], [80], are extracted from continuous WT (CWT), discrete WT (DWT), and wavelet packet transforms (WPT). These are used to detect imbalance, misalignment, spalling, pitting in gears, faulty bearings, and OLTC [96]. Contrary to WT, EMD is a self-adaptive method, applied to fault diagnosis for the first time in 1998. EMD decomposes the signal into a sum of intrinsic mode functions (IMFs). The frequency components in each IMF are related to the sampling frequency and to the signal itself, whereas WT is related only to the sampling frequency. However, the number of IMFs cannot be controlled [34], [62], [90]. The HHT uses the EMD to obtain IMFs [20], [34], and then EnA is applied to each IMF using the HT.

Many new techniques have, in the last six years, been proposed in time–frequency analysis. Most of them are related to the decomposition of the signal into mono-component AM–FM signals (amplitude- and frequency-modulated signals) which are then analyzed using EnA techniques, and to the improvements in WT and EMD techniques. These techniques allow a finer analysis of the signal and more accuracy to detect single and compound faults, essential in fault diagnosis. They are discussed in the following paragraphs.

Spectral kurtosis (SK) is a spectral statistic reformulated in 2006 for nonstationary signals [103]. SK provides a robust way of detecting incipient faults that produce impulse-like signals, even in the presence of strong noise. SK also offers a way of designing optimal filters for filtering out the mechanical signature of faults using the kurtogram or the fast kurtogram (ways to compute the SK) as a prelude to EnA [104]. Local mean decomposition (LMD) and improved LMD are also proposed for fault diagnosis [109]. Contrary to the HHT, LMD does not use HT to estimate the envelope but uses the moving average. Product functions are obtained by multiplying the envelope estimates and the FM signal. Generalized demodulation time frequency (GDTF) also decomposes the signal into mono-component AM–FM signals, transforming the original signal into a new space where WT can be applied, therefore, obtaining frequencies with physical meaning. The envelope order spectrum technique, which blends GDTF and the spectrum, has also been proposed for fault diagnosis [98]. Iterated Hilbert transform (ItHT) analyzes AM–FM signals using the iterated application of the HT to a filtered version of the amplitude envelope. Amplitude envelopes and instantaneous frequencies are then extracted. ItHT has higher demodulation accuracy and lower complexity than EMD. The combination of ItHT and a smoothed instantaneous frequency estimation has been recently applied to fault diagnosis [105]. Ensemble EMD (EEMD) is a novel technique (2009) that eliminates the mode-mixing problem in EMD. In the mode-mixing problem, the physical meaning of each IMF is unclear and EMD fails to represent the fault characteristics of a signal accurately. EEMD uses a noise-assisted technique to eliminate the mode-mixing problem. EEMD and EMD are applied to a rotor fault and in a heavy oil catalytic cracking machine set [42]. Results show that EEMD can extract the fault characteristic information better than EMD. The multiscale enveloping spectrogram (MuSEnS) [45] algorithm was developed in 2009 using time, scale, and frequency domain information contained in the signal. It decomposes the signal into different wavelet scales and the envelope signal in each scale is calculated, resulting in an ''envelope spectrum'' [45].

Second-generation WT (SGWT) [110] was proposed in 2006 and overcomes the main shortcoming of the WT (the proper selection of the mother wavelet) because SGWT is realized by a lifting scheme in the time domain (which is not based on the Fourier transform). The improved WPT (IWPT) is also based on SGWT and it is shown to be superior to WPT in extracting the fault characteristics in bearings [43], [67]. An approach that improves the SGWT is the redundant SGWT (RSGWT) proposed in 2009 [107], [110]. RSGWT is time-invariant, contrary to SGWT, which allows capturing more useful fault information. RSGWT outperforms SGWT in extracting transient components in gearbox vibration signals [110]. The dual-tree complex WT (dtcWT) was proposed in 2010 [93] in fault diagnosis. In [93], the authors show that dtcWT outperforms SGWT, fast kurtogram, and DWT because dtcWT enhances noise reduction, is approximately time invariant, and can detect multiple fault features simultaneously [93]. Another application of the WT includes a novel growth index [46], insensitive to different mother wavelets and

levels of decomposition. Finally, the generalized *S* transform was proposed in 2011 for fault diagnosis. It unifies STFT and WT so as to obtain more satisfactory time–frequency representations than other similar techniques, such as STFT, WVD, and *S* transform. This allows more accurate detection of the bearing fault characteristic [106].

4) *Nonlinear Analysis:* Evidence of a complex and nonlinear vibratory system has been found in stator-rotor rub, loose pedestal, and unstable oil film faults [17]. Conventional nonlinear methods include pseudo-phase portrait, singular spectrum analysis, correlation dimension (CD) [22], fractal dimensions, approximate entropy (ApEn), information entropy [91], mutual information [24], and Lyapunov exponents [13], [108]. CD quantifies the complexity of a time series and has successfully proven to detect rotor-stator rub, loose pedestal faults [22], and bearing faults [17], [21]. Phase portrait shows qualitative differences in a normal gear and in a gear with an early fatigue cracked tooth [9]. ApEn quantifies the regularity of a time series and can effectively indicate the condition in fans [47] and bearings with speed and load variations [48].

A new technique is proposed in [23] to select a proper fractal dimension spectrum less affected by noise. In a more recent paper (2008) [50], a modification of the correlation integral is introduced to the real-time fault diagnosis of bearings. Multiple manifold analysis is a novel nonlinear approach [108] (2009) that extracts manifold information from the vibration signals and outperforms conventional nonlinear techniques. A paper of 2010 proposes to compute the fractal dimension using DWT [94]. Fractal features are estimated from the slope of the variances of the DWT in different scales.

### B. Audio Signal Processing

Most research in machinery diagnosis is oriented toward the analysis of vibration signals. Audio-based CM has, however, not developed at the same rate**.** This is due to the contamination of the sound signal by unwanted sources, such as other machines, noisy environments, and the structural vibration of the machine itself [1]. This situation makes it difficult to acquire the machine's signature. Two main options are used to improve the low SNR in audio signals: the use of partial or full enclosure using an anechoic chamber [6], [14], which is an unrealistic approach for real industrial scenarios, or the use of preprocessing denoising methods, such as wavelet [11] or blind source separation [1], [14], [25]. These techniques can affect the feature extraction stage. The choice of certain parameters, such as the threshold in wavelet techniques, is important for the extraction of the purified signal with the smallest distortion and the highest SNR. Audio-based techniques are useful in certain cases, especially when it is impossible to access the machine. Audio measurements can be performed at a distance from the machine so the use of sensors mounted directly on the machine is avoided.

The same processing techniques for vibrations are applied to extract features in audio signals obtained from machines. Statistical time domain features and energy features in the frequency domain [58] are used to detect wear in internal combustion engines and mass unbalance faults in rotary disks.

EnA is used in a heavy sizing-press [25] and in the end-test of vacuum cleaner production [57], where the use of vibration and current analysis did not prove useful. As in vibration-based techniques, the audio spectrum is used when the machine is working at constant speeds [9], [55]. Some papers compare the use of Fourier analysis in audio and vibration signals [9], [86]. These works claim that the Fourier analysis is less effective in sound signals because of the low SNR. As in the case of vibration analysis, time–frequency techniques are more appropriate. For example, STFT is applied to identify engine fault frequencies [53]. However, WVD [85] and pseudo-WVD [55] are shown to have better results in extracting nonstationary signatures in the bearings of induction motors. CWT, WPT, and MFCC are successfully applied to fault diagnosis of engines [14], [51], [56] working at different speeds and run-up conditions.

The symmetrized dot pattern technique is based on the visualization of changes in amplitude and frequency of the audio signal. It has been applied to distinguish between normal and faulty fans [9] and in the fault identification of an internal combustion engine working at different speeds [54]. Some papers have focused on the analysis of a group of chaotic measures extracted from audio signals of different machines. Asynchronous changes in audio signals can be detected with chaotic measures [24]. The spectral entropy of audio signals has shown to be more effective than vibration signals in the diagnostic of cavitation [87].

The development of techniques to improve SNR and the use of the same tool, i.e., wavelets, in the denoising and extraction stages can put audio-based techniques at an advantageous position in CM systems since they are less intrusive than vibration-based techniques.

Multiple features are extracted from vibration and audio signals in CM techniques. However, a unique feature capable of representing the machine condition does not exist. A good characterization requires the extraction of different features from different domains. Thus, we need to find, using feature selection, the most suitable ones for the application under consideration. The selection of well-suited features providing fault-related information and the discarding or weakening of irrelevant or redundant features is an important stage in machine CM to improving system performance.

## IV. DECISION STAGE

The decision support stage of CM systems helps take maintenance actions when a fault is impending or already detected. The decision stage can be performed by a qualified person or an expert system. This paper focuses on pattern recognition techniques applied to machine CM. Automatic pattern recognition techniques can be accomplished using supervised or unsupervised learning. In supervised learning, the machine should be forced to work in different conditions, including faulty states, to train the pattern recognition system. Alternatively, unsupervised learning methods (or novelty detection), only require normal data and it is not necessary to damage the machine. However, novelty methods can only distinguish between normal and faulty conditions. Noise and

TABLE III
CLASSIFICATION METHODS FOR VIBRATION AND AUDIO

| Methods | Evolution | | | |
|---|---|---|---|---|
| | 1980–1999 | 2000–2003 | 2004–2007 | 2008–2012 |
| SPC | [81] (V, U) | [26] (V, U) | — | — |
| Distances | | [65] (V, S) | — | [66](V,U); [34] (V, S) |
| SVM, SVDD, PSVM | — | — | [69] (V, U); ([43], [51]) (V, S); [100] (V,S) | [67] (V, U); [90] (V, S); [92] (V,S) |
| HMM | — | — | [28] (V, U); [23] (V, S) | — |
| Hyp. test, GMM | | [64] (V) | [39] (V) | [36] (V) |
| NN | — | — | [68] (V, U) | [34], [44], [62], [63] (V, S); [56] (A, S); [60] (V, U) |
| Fuzzy-logic | — | — | [12] (V, S) | [59] (V, S) |
| Evolutionary alg. | — | — | [38] (V, S) | [34] (V, S) |
| Expert systems | — | — | [58] (A, S); [89] (V,S) | [62], [111] (V, S) |

V, vibration; A, audio; S, supervised; U, unsupervised.

the changing environment must also be taken into account to avoid incorrect interpretations. Below, pattern recognition techniques used in fault diagnosis are discussed. Table III presents some of the most common classification methods used in the literature.

Statistical process control (SPC) is a conventional unsupervised method that measures the deviation of the current signals from a reference signal (which represents the normal condition) to determine whether the current signal is inside the control limits [26], [81]. Cluster analysis groups signals into different fault categories according to the similarity of the features. The objective is to minimize the variance inside the same group and to maximize it between different groups. Conventional distances used to achieve this objective are: Mahalanobis distance [65], Euclidean distance [34], [65], and Bayesian distance [65]. In 2008, [66] proposed a novel clustering algorithm using a compensation distance evaluation technique in unsupervised clustering. The support vector machine (SVM) is a cluster-based technique widely used in machinery diagnosis [43], [51], [92]. It maximizes the distance of the closest point to the boundary curve that separates two data classes. The original SVM performs bi-class classification but multiclass SVMs have been developed to classify different kinds of faults [43]. Proximal SVM (PSVM) has also been proposed in fault diagnosis [100]. PSVM is modeled as a system of linear equations, which produces results similar to SVM, but with less computational effort. In 2005, the application of one-class SVM was proposed in fault diagnosis. One-class SVM is an unsupervised technique [69] based on the support vector data description (SVDD). It fits a tight hypersphere around the feature vector extracted from normal signals. This method has been used in bearing degradation experiments [67]. SVDD for multiclass classification was proposed in 2009 [90]. It uses the centers of a set of hyperspheres and models the decision boundaries via a combination of linear discriminant analysis and the nearest-neighbor rule.

HMM is a conventional method used to perform fault classification by analyzing the time series. The hidden states of the Markov model represent healthy and faulty states [27], although in the latest developments, the relationship between hidden states and physical meaning is not established [28]. The factorial HMM classifier has a strong capability for classification of nonstationary signals. For this reason, factorial

HMM was applied in 2006 for the speed-up and speed-down process [61]. In 2007, an HMM was used in unsupervised learning mode for fault detection [23].

Statistical hypothesis tests, such as the Kolmogorov–Smirnov test [36], [64] and Student's *t*-test [64] have been conducted to statistically compare signatures of normal and faulty machinery. Density estimation techniques are also popular in fault detection. These are unsupervised methods that model the underlying distribution of the data. The Gaussian mixture model (GMM) analyzes features extracted from a signal using a weighted sum of Gaussians. The success of GMM in the classification of dynamic data makes GMM especially suitable in modeling vibration data from machinery. GMM was applied for the first time to fault diagnosis in 2006 [39].

Neural networks (NNs), fuzzy-logic (FL), expert systems, and evolutionary algorithms are pattern recognition techniques widely used in fault diagnosis. They are usually utilized in a blended way to obtain better performance. Because of their high learning and generalizing capabilities, NNs are used to classify different machinery faults [84], [92]. The NN is a conventional classification method and multiple NN models, such as multilayer perceptron [34], [62], radial basis functions [34], [63], back-propagation NN [56], probabilistic NN [44], generalized regression NN [56], and wavelet NN [63] have been used in fault diagnosis. Auto-associative NNs [68] and self-organizing maps [60] are unsupervised conventional NN techniques applied in diagnosis. FL and decision trees have been combined to generate rules from the feature set automatically [59]. The combination of NN and FL improves the learning capabilities at the self-adaption and self-learning stages [12], [88]. The neuro-fuzzy approach aims at automating the design of a fuzzy system using NN. An extended neuro-fuzzy system was proposed in 2008 for CM [112]. NN, FL, and a decision tree algorithm are used together in [59].

Expert systems use the knowledge of an expert in a computer program. The knowledge base contains domain knowledge, while the inference mechanism manipulates the knowledge to produce solutions [89]. When the expert knowledge is inexact, FL obtains uncertainty measures [12]. An NN inference mechanism is used in an expert system to diagnose unbalances using acoustic signals [58]. Recent papers have focused on a new adaptive neuro-fuzzy inference system (ANFIS) that combines the FL approach and the adaptive NN

TABLE IV

SYSTEMS PERFORMANCE

| Refs. | Main features | Database | Approach | Results |
|---|---|---|---|---|
| Lei *et al.* [62] (V) | Time and frequency domains, EMD | Bearing vibration dataset [70] (N, OR, IR, B faults) | ANFIS | 100% Training: 140, Test: 70 |
| Yu *et al.* [44] (V) | DWT (cluster-based feature extraction) | Bearing vibration dataset [70] (N, OR, IR, B faults) | Probabilistic NN | 98.2% (maximum accuracy)Training: 168, Test: 60 |
| Sanz *et al.* [68] (V) | Discrete wavelet transform | Pump vibration database [73] (gears) (N and damage pump), (two loads) | Auto-associative NN (unsupervised mode) | 100%, Training: 650 (N); Test: 160 (N), 810 (damage) |
| Cho *et al.* [77] (V) | Time and frequency domain; Parameters: speed, feed and depth of cut | OKUMA ES 3016 CNC vertical machining center (N, breakage, chipping, wear), (different speeds) | SVM, multilayer perceptron, radial basis function | 97.67% (maximum accuracy with three-sensor combination) |
| Wang *et al.* [75] (V) | Wavelet energy function, phase demodulation, kurt. | Gears (N, cracked, and chipped) | Neural fuzzy scheme | 97.6% |
| Wu *et al.* [56] (A) | Shannon entropy of wavelet package transform coefficients | Internal combustion engine (N, 5 faulty conditions) (2 fixed speeds and a run-up experiment) | Generalized regression NN | >95% in all experiments, Training: 30 for each condition, Test: 120 for each condition |

V, vibration; A, audio; N, normal condition; OR, outer race fault; IR, inner race fault; B, ball fault.

capability [62]. Recently, the soft set theory, a mathematical tool used to deal with uncertainties, has been applied for the first time in fault diagnosis (2012) [111].

Finally, in artificial techniques, evolutionary algorithms have been used to reproduce the natural process of the evolution of a population. The most frequently used are genetic algorithms which are applied to fault diagnosis to select the more adequate and competitive features and to combine different classifiers to obtain better performance [34], [38].

## V. SYSTEMS AND PERFORMANCE

This section discusses the performance evaluation techniques in diagnostic technologies and shows examples of the application of CM systems. The use of performance metrics allows different algorithms and techniques to be compared so as to evaluate the entire CBM system. The creation of a common performance evaluation framework is a challenging task for researchers and standards institutions and organizations; ISO 17359 outlines the CM metrics and the Society of Automotive Engineers (SAE) [30] addresses all aspects of metrics. The NASA Ames Research Center proposes an annual international diagnostic competition (http://dx-competition.org/) to discuss the latest developments.

The metrics used in diagnostic/prognostic technologies can be divided into performance metrics and effectiveness metrics. Performance metrics assess technical performance, such as algorithm performance, while effectiveness metrics measure the capability of the global system to achieve operational goals. Most metrics used in the literature include classification accuracy, true positive (TP, percentage of correct classification), false positive (FP, percentage of incorrect classification), false negative (FN, number of misses), true negative (TN number of correct rejections), the confusion matrix (a representation of TP, FP, FN, and TN) [59], [60] and the receiving operating curve (ROC) [60]. ROC gives a comprehensive overview of the trade-off between FP and FN.

Some authors and institutions have developed test beds to assess the performance and effectiveness of the proposed metrics for diagnostic systems [31]–[33]. The NASA Ames Research Center developed a real-world electrical power system test bed [31] and the U.S. Navy [32] developed a CBM test bench with data provided by the State ARL Mechanical Diagnostics Test Bed (MDTB) [72].

The fault diagnosis techniques proposed in the literature cannot be easily compared because of the lack of common and public machinery databases. Some efforts have been made to develop public databases, although there is only a limited number of them: Case Western Reserve University [70] provides bearing vibration signals, Ypma provides normal and faulty samples of pumps [73], the NASA Prognostics Data Repository includes a collection of donated datasets [74], the Naval Systems Command provides vibration signals of an UH-60 helicopter [71], and the MDTB data [72] of gears, shaft, and bearings can be obtained under previous petition.

Table IV summarizes the characteristics of some CM systems based on vibration or audio analysis. Performance evaluation of most of these systems is made using classification accuracy. Yu *et al.* [44] and Lei *et al.* [62] use the Case Western University bearing vibration dataset [70]. A 100% accuracy is obtained in [62] using a set of selected features from time, frequency, and time–frequency domain. The improved distance evaluation technique is used to select the most suitable features that feed the ANFIS. Yu *et al.* [44] use an unsupervised procedure based on cluster-based feature extraction from DWT and probabilistic NN. Different scales of WT decomposition are used and the classification accuracy is computed for each scale. Sanz *et al.* [68] apply WT and unsupervised auto-associative NN in a gearbox of a pump station [73] with the data collected by Ypma. Cho *et al.* [77] and Wang *et al.* [75] propose automatic fault diagnosis systems applied to real industrial scenarios. Cho *et al.* [77] propose a CM system in an end milling machine. Multiple sensors, including vibration sensors, are used and features from the frequency

domain are extracted. Fusion at feature and decision levels is performed. Wang *et al.* [75] propose a real-time CM system for gears in printing machines. Wu *et al.* [56] use audio signals in the development of an expert system for internal combustion engines. Shannon entropy is extracted from WPT. Back propagation NNs and generalized regression NNs were used as classification methods achieving a success rate of 95%.

Most CM products on the market are directed to specific applications so the results of using a prototype are not generally reproducible for other applications. For this reason, the use of standards is recommended. Two standards and two standardization proposals can be found in: IEEE 1451 and IEEE 1232, and MIMOSA and OSA-CBM [76].

## VI. DISCUSSION AND CONCLUSION

Nowadays, machinery diagnosis implementing CBM is a field of intensive research. A good CBM policy leads to the detection and prevention of faults. Companies can save millions of dollars per year and human lives with a well-implemented CM system. The need for increasing security in industrial scenarios and the rapid development of signal processing techniques and communication technologies have helped scientific and technological advancements in this field. This paper presented a review of vibration- and audio-based automatic fault diagnosis in machinery implementing the stages of a CBM system (data acquisition, signal processing, and decision-making). This paper paid special attention to recent advancements in signal processing techniques and classification methods. Finally, some examples of CM systems were presented.

Vibration-based monitoring is a well-established technique widely used in CBM. Audio-based monitoring, though, has not been applied to CBM systems to the same degree, even though microphones are not mounted on the machine and there are greater location possibilities. The main reason is the difficulty of recovering the machine's signature because the signal is usually immersed in noise. Denoising techniques and source separation algorithms are used to alleviate the noise effect. However, these techniques have to be improved to obtain better results. A promising research line in audio-fault diagnosis is the development of better algorithms for source separation. This can also be extended to the vibration signal. Moreover, the application of audio-fault diagnosis techniques in an extensive way will improve greatly the inspection of certain industrial environments in which a permanent CM system is expensive or the mounting of vibration sensors is difficult. For this reason, we think audio-based techniques need further research efforts.

Signal processing techniques have evolved from conventional time and frequency analysis, which assume stationarity and linearity, to more developed techniques that exploit the nonstationary and nonlinear nature of faulty signals and of speed-up and speed-down processes. These provide a more realistic description of the real condition of the machine. In this paper, multiple features from vibration-based diagnosis were described. Most of them are not used in audio-based diagnosis. As a future research line, we propose the application

of vibration features to audio signals and a comparison of the performance in both cases. The classification techniques used in the decision-making stage have evolved toward intelligent, adaptive, and faster algorithms, leading to more robust and real-time monitoring systems. However, further research is required to obtain fault diagnosis systems capable of diagnosing compound faults.

There is a lack of both benchmarking and large databases in fault diagnosis. The collaboration of industry and researchers is essential to create large, publicly available databases of machines working in real scenarios. The access to real data in the industrial environment for research purposes benefits both sides. Public databases provide common data to comparatively evaluate fault diagnosis techniques and CM systems. The use of a common framework of performance metrics is also necessary for this task. Although researchers and industry have defined performance metrics, their application in scientific research is still poor.

In case of unavailable fault data, unsupervised classification methods are a good alternative. Further research is needed to model data from normal conditions, taking into account different conditions, noisy samples, and environmental changes. The improvement of unsupervised modeling, using GMMs or SVDD, and the application of the universal background model in fault diagnosis, where much data from normal conditions is available, are promising research lines.

Data fusion of multiple data are a clear research line in fault diagnosis. Data fusion at signal, feature, and decision levels can result in more reliable CM systems. Moreover, a joint analysis of the machine's signature, process control data (i.e., information about power consumption or load conditions), and event data (i.e., information about maintenance adjustments and operational changes) will improve the robustness, accuracy, and sensitivity of CM systems.

Further research is definitely needed in machinery diagnosis to develop more robust and reliable systems in industrial scenarios. The use of different kinds of data, artificial intelligence techniques, sensor fusion, micro-technology, and communication will lead this field toward onboard, intelligent, and interconnected systems.

## REFERENCES

[1] R. M. Vilela, J. C. Metrôlho, and J. C. Cardoso, "Machine and industrial monitorization system by analysis of acoustic signatures," in *Proc. 12th IEEE Mediterranean Electrotech. Conf.*, Dubrovnik, Croatia, May 2004, vol. 1, pp. 277–279.

[2] D. Basak, A. Tiwari, and S. P. Das, "Fault diagnosis and condition monitoring of electrical machines—A review," in *IEEE Int. Conf. Ind. Technol.*, Mumbai, Dec. 15–17, 2006, pp. 3061–3066.

[3] A. K. S. Jardine, D. Lin, and D. Banjevic, "A review on machinery diagnostics and prognostics implementing condition-based maintenance," *Mech. Syst. Signal Process.*, vol. 20, no. 7, pp. 1483–1510, Oct. 2006.

[4] S. Nandi, "Condition monitoring and fault diagnosis of electrical motors—A review," *IEEE Trans. Energy Conver.*, vol. 20, no. 4, Dec. 2005.

[5] G. Vachtsevanos, F. L. Lewis, M. Roemer, A. Hess, and B. Wu, *Intelligent Fault Diagnosis and Prognosis for Engineering Systems*, 1st ed. Hoboken, NJ, USA: Wiley Inc., 2006.

[6] N. Tandon and A. Choudhury, "A review of vibration and acoustic measurement methods for the detection of defects in rolling element bearings," *Tribol. Int.*, vol. 32, no. 8, pp. 469–480, Aug. 1999.

[7] S. W. Doebling, C. R. Farrar, and M. B. Prime, "A summary review of vibration-based damage identification methods," *Short Vibration Dig.*, vol. 30, no. 2, pp. 91–105, 1998.

[8] H. Yang, J. Mathew, and M. Lin, "Vibration feature extraction techniques for fault diagnosis of rotating machine: A literature survey," in *Asia-Pacific Vibration Conf.*, Australia, Nov. 12–14, 2003, pp. 12–14.

[9] K. Shibata, A. Takahashi, and T. Shirai, "Fault diagnosis of rotating machinery through visualisation of sound signals," *Mech. Syst. Signal Process.*, vol. 14, no. 2, pp. 229–241, Mar. 2000.

[10] W. J. Wang and R. M. Lin, "The application of pseudo-phase portrait in machine condition monitoring," *J. Sound Vibration*, vol. 259, no. 1, pp. 1–16, Jan. 2003.

[11] N. Baydar and A. Ball, "Detection of gear failures via vibration and acoustic signals using wavelet transform," *Mech. Syst. Signal Process.*, vol. 17, no. 4, pp. 787–804, Jul. 2003.

[12] K. Shanlin, P. Peilin, F. Feng, and D. Guangbin, "Feature extraction method in fault diagnosis based on wavelet fuzzy network for power system rotating machinery," in *Proc. 26th Chin. Control Conf.*, Zhangjiajie, China, July 26–31, 2007, pp. 437–441.

[13] P. C. Moller, J. Bajkowski, and D. Soffker, "Chaotic motions and fault detection in a cracked rotor," *Nonlinear Dyn.*, vol. 5, no. 2, pp. 233–254, Mar. 1994.

[14] Z. M. Zhong, J. Chen, P. Zhong, and J. B. Wu, "Application of the blind source separation method to feature extraction of machine sound signals," *Int. J. Adv. Manuf. Technol.*, vol. 28, nos. 9–10, pp. 855–862, Jul. 2006.

[15] P. D. McFadden and J. D. Smith, "Vibration monitoring of rolling element bearings by high freq. resonance technique—A review," *Tribol. Int.*, vol. 77, no. 1, pp. 3–10, Feb. 1984.

[16] D. M. Yang, A. F. Stronach, O. Macconnell, and J. Penman, "Third-order spectral techniques for the diagnosis of motor bearing condition using artificial neural network," *Mech. Syst. Signal Process.*, vol. 16, nos. 2–3, pp. 391–411, Mar. 2002.

[17] W. J. Wang, Z. T. Wu, and J. Chen, "Fault identification in rotating machinery using the correlation dimension and bispectra," *Nonlinear Dyn.*, vol. 25, no. 4, pp. 383–393, Aug. 2001.

[18] Y.-C. Choi and Y.-H. Kim, "Fault detection in a ball bearing system using minimum variance cepstrum," *Meas. Sci. Technol.*, vol. 18, no. 5, pp. 1433–1440, May 2007.

[19] Z. K. Peng, F. L. Chu, and P. W. Tse, "Singularity analysis of the vibration signals by means of wavelet modulus maximal method," *Mech. Syst. Signal Process.*, vol. 21, no. 2, pp. 780–794, Feb. 2007.

[20] Z. K. Peng, P. W. Tse, and F. L. Chu, "A comparison study of improved Hilbert–Huang transform and wavelet transform: Application to fault diagnosis for rolling bearing," *Mech. Syst. Signal Process.*, vol. 19, no. 5, pp. 974–988, Sep. 2005.

[21] D. Logan and J. Mathew, "Using the correlation dimension for vibration fault diagnosis of rolling element bearing—2. Selection of experimental parameters," *Mech. Syst. Signal Process.*, vol. 10, no. 3, pp. 251–264, May 1996.

[22] W. J. Wang, J. Chen, and Z. T. Wu, "The application of correlation dimension in large rotating machinery fault diagnosis," *ImechE, J. Mech. Eng. Sci. C*, vol. 214, no. 7, pp. 921–929, Jul. 2000.

[23] T. Xinmin, D. Baoxiang, and X. Yong, "Bearing fault diagnosis based on HMM and fractal dimensions spectrum," in *Proc. IEEE Int. Conf. Mechatronics Automat.*, Harbin, China, Aug. 5–8, 2007.

[24] P. Henríquez, J. B. Alonso, C. M. Travieso, and M. A. Ferrer, "Advances in automatic detection of failures in electric machines using audio signals," in *Proc. 11th IASTED Int. Conf. Artif. Intell. Soft Comput.*, Palma de Mallorca, Spain, Aug. 29–31, 2007, pp. 114–119.

[25] L. Li and L. Qu, "Machine diagnosis with independent component analysis and envelope analysis," *IEEE Int. Conf. Ind. Technol.*, Bangkok, Dec. 2000, vol. 2, pp. 1360–1364.

[26] M. L. Fugate, H. Sohn, and C. R. Farrar, "Vibration-based damage detection using statistical process control," *Mech. Syst. Signal Process.*, vol. 15, no. 4, pp. 707–721, Jul. 2001.

[27] C. Bunks, D. McCarthy, and T. Al-Ani, "Condition-based maintenance of machines using hidden Markov models," *Mech. Syst. Signal Process.*, vol. 14, no. 4, pp. 597–612, Jul. 2000.

[28] Z. Li, Z. Wu, Y. He, and C. Fulei, "Hidden Markov model-based fault diagnostics method in speed-up and speed-down process for rotating machinery," *Mech. Syst. Signal Process.*, vol. 19, no. 2, pp. 329–339, Mar. 2005.

[29] W. Wang and A. K. Wong, "Autoregressive model-based gear fault diagnosis," *J. Vibration Acoustics*, vol. 124, no. 2, pp. 172–179, Mar. 2002.

[30] SAE (Society of Automotive Engineers) E-32, 2007, "Health and Usage Monitoring Metrics, Monitoring the Monitor", SAE ARP 5783-DRAFT, Feb. 14, 2007.

[31] T. Kurtoglu, O. Mengshoel and S. Poll, "A framework for systematic benchmarking of monitoring and diagnostic systems," *Int. Conf. Prognostics Health Manage.*, Denver, Oct. 6–9, 2008, pp. 1–13.

[32] T. Kurtoglu, S. Narasimhan, S. Poll, D. Garcia, L. Kuhn, J. de Kleer, A. van Gemund, and A. Feldman, "Towards a framework for evaluating and comparing diagnosis algorithms," in *Proc. 20th Int. Workshop Principles Diagn (DX'09)*, Stockholm, SE, 2009.

[33] M. J. Roemer, J. Dzakowic, R. F. Orsagh, C. S. Byington, and G. Vachtsevanos, "Validation and verification of prognostic health management technologies," *IEEE Conf. Proc.*, Big Sky, MT, March 5–12, 2005, pp. 3941–3947.

[34] Y. Lei, M. J. Zuo, Z. He, and Y. Zi, "A multidimensional hybrid intelligent method for gear fault diagnosis," *Expert Syst. Appl.*, vol. 37, no. 2, pp. 1419–1430, Mar. 2010.

[35] X. Wang, V. Makis, and M. Yang, "A wavelet approach to fault diagnosis of a gearbox under varying load conditions," *J. Sound Vibration*, vol. 329, no. 9, pp. 1570–1585, Apr. 2010.

[36] Y. Shao and C. K. Mechefske, "Gearbox vibration monitoring using extended Kalman filters and hypothesis tests," *J. Sound Vibration*, vol. 325, no. 3, pp. 629–648, Aug. 2009.

[37] F. L. Wang and C. K. Mechefske, "Adaptive modelling of transient vibration signals," *Mech. Syst. Signal Process.*, vol. 20, no. 4, pp. 825–842, May 2006.

[38] W. Dou, Z.-S. Liu, and D.-H. Wang, "Combination diagnosis based on genetic algorithm for rotating machinery," in *Proc. 3rd Int. Conf. Nat. Computation*, Harbin, China, Aug. 2007, pp. 307–313.

[39] F. V. Nelwamondo and T. Marwala, "Faults detection using gaussian mixture models, Mel-frequency cepstral coefficients and kurtosis," presented at the IEEE Int. Conf. Syst., Man Cybern., Taiwan, Oct. 8–11, 2006.

[40] I. S. Koo and W. W. Kim, "The development of reactor coolant pump vibration monitoring and a diagnostic system in the nuclear power plant," *ISA Trans.*, vol. 39, no. 3, pp. 309–316, Jul. 2000.

[41] S. U. Lee, D. Robb, and C. Besant, "The directional Choi–Williams distribution for the analysis of rotor-vibration signals," *Mech. Syst. Signal Process.*, vol. 15, no. 4, pp. 789–811, Jul. 2001.

[42] Y. Lei, Z. He and Y. Zi, "Application of the EEMD method to rotor fault diagnosis of rotating machinery," *Mech. Syst. Signal Process.*, vol. 23, no. 4, pp. 1327–1338, May 2009.

[43] Q. Hu, Z. He, Z. Zhang, and Y. Zi, "Fault diagnosis of rotating machinery based on improved wavelet package transform and SVMs ensemble," *Mech. Syst. Signal Process.*, vol. 21, no. 2, pp. 688–705, Feb. 2007.

[44] G. Yu, C. Li, and S. Kamarthi, "Machine fault diagnosis using a cluster-based wavelet feature extraction and probabilistic neural networks," *Int. J. Adv. Manuf. Technol.*, vol. 42, nos. 1–2, pp. 145–151, May 2009.

[45] R. Yan and R. X. Gao, "Multi-scale enveloping spectrogram for vibration analysis in bearing defect diagnosis," *Tribol. Int.*, vol. 42, no. 2, pp. 293–302, Feb. 2009.

[46] D. Wang, Q. Miao, and R. Kang, "Robust health evaluation of gearbox subject to tooth failure with wavelet decomposition," *J. Sound Vibration*, vol. 324, nos. 3–5, pp. 1141–1157, Jul. 2009.

[47] J. Tan, J.-J. Gu, X.-Z. Peng, and Z.-M. Qin, "A fault diagnosis method based on wavelet approximate entropy for fan," *Proc. 6th Int. Conf. Mach. Learn. Cybern.*, Hong Kong, Aug. 19–22, 2007, pp. 519–523.

[48] R. Yan and R. X. Gao, "Approximate entropy as a diagnostic tool for machine health monitoring," *Mech. Syst. Signal Process.*, vol. 21, no. 2, pp. 824–839, Feb. 2007.

[49] H. Li, L. Fu, and Y. Zhang, "Bearing faults diagnosis based on Teager energy operator demodulation technique," *Int. Conf. Meas. Technol. Mechatronics Automation*, Zhangjiajie, China, April 11–12, 2009, pp. 594–597.

[50] S. Janjarasjitt, H. Ocak, and K. A. Loparo, "Bearing condition diagnosis and prognosis using applied nonlinear dynamical analysis of machine vibration signal," *J. Sound Vibration*, vol. 317, nos. 1–2, pp. 112–126, Oct. 2008.

[51] J. Yang, Y. Zhang, and Y. Zhu, "Intelligent fault diagnosis of rolling element bearing based on SVMs and fractal dimension," *Mech. Syst. Signal Process.*, vol. 21, no. 5, pp. 2012–2024, Jul. 2007.

[52] V. Singh and N. Meena, "Engine fault diagnosis using DTW, MFCC and FFT," in *Proc. 1st Int. Conf. Intell. Human Comput. Interaction*, Allahabad, India, Jan. 2009, pp. 83–94.

[53] A. B. Mansoor, H. Ahmed, and Z. Mahmood, "Design and development of an automated acoustic based jet engine performance evaluator," in *Proc. IEEE Int. Conf. Ind. Technol.*, Gippsland, VIC, Feb. 10–13, 2009, pp. 1–4.

[54] J.-D. Wu and C.-Q. Chuang, "Fault diagnosis of internal combustion engines using visual dot patterns of acoustic and vibration signals," *NDT&E Int.*, vol. 38, no. 8, pp. 605–614, Dec. 2005.

[55] W. Li and C. K. Mechefske, "Detection of induction motor faults: A comparison of stator current, vibration and acoustic methods," *J. Vibration Control*, vol. 12, no. 2, pp. 165–188, Feb. 2006.

[56] J.-D. Wu and C.-H. Liu, "An expert system for fault diagnosis in internal combustion engines using wavelet packet transform and neural network," *Expert Syst. Appl.*, vol. 36, no. 3, pp. 4278–4286, Apr. 2009.

[57] U. Benko, J. Petrovcic, D. Juricic, J. Tavcar and J. Rejec, "An approach to fault diagnosis of vacuum cleaner motors based on sound analysis," *Mech. Syst. Signal Process.*, vol. 19, no. 2, pp. 427–445, Mar. 2005.

[58] W. Li, Y. P. Tsai, and C. L. Chiu, "The experimental study of the expert system for diagnosing unbalances by ANN and acoustic signals," *J. Sound Vibration*, vol. 272, nos. 1–2, pp. 69–83, Apr. 2004.

[59] N. R. Sakthivel, V. Sugumaran, and B. B. Nair, "Comparison of decision tree-fuzzy and rough set-fuzzy methods for fault categorization of mono-block centrifugal pump," *Mech. Syst. Signal Process.*, vol. 24, no. 6, pp. 1887–1906, Aug. 2010.

[60] P. Ballal, A. Ramani, M. Middleton, C. McMurrough, A. Athamneh, W. Lee, C. Kwan, and F. Lewis, "Mechanical fault diagnosis using wireless sensor networks and a two-stage neural network classifier," in *Proc. IEEE Aerosp. Conf.*, TX, Mar. 2009, pp. 1–10.

[61] Z. Li, Y. He, F. Chu, J. Han, and W. Hao, "Fault recognition method for speed-up and speed-down process of rotating machinery based on independent component analysis and factorial hidden Markov model," *J. Sound Vibration*, vol. 291, nos. 1–2, pp. 60–71, Mar. 2006.

[62] Y. Lei, Z. He, and Y. Yi, "A new approach to intelligent fault diagnosis of rotating machinery," *Expert Syst. Appl.*, vol. 35, no. 4, pp. 1593–1600, Nov. 2008.

[63] L. Wei and H. Pu, "Wavelet neural network aided on-line detection and diagnosis of rotating machine fault," in *Proc. Chin. Control Decision Conf.*, Handan, China, Jul. 2008, pp. 1868–1871.

[64] C. Kar and A. R. Mohanty, "Application of KS test in ball bearing fault diagnosis," *J. Sound Vibration*, vol. 269, no. 1–2, pp. 439–454, Jan. 2004.

[65] S. K. Goumas, M. E. Zervakis, and G. S. Stavrakakis, "Classification of washing machines vibration signals using discrete wavelet analysis for feature extraction," *IEEE Trans. Instrum. Meas.*, vol. 51, no. 3, pp. 497–508, Jun. 2002.

[66] Y. Lei, Z. He, Y. Zi, and X. Chen, "New clustering algorithm-based fault diagnosis using compensation distance evaluation technique," *Mech. Syst. Signal Process.*, vol. 22, no. 2, pp. 419–435, Feb. 2008.

[67] Y. Pan, J. Chen, and L. Guo, "Robust bearing performance degradation assessment method based on improved wavelet packet—Support vector data description," *Mech. Syst. Signal Process.*, vol. 23, no. 3, pp. 669–681, Apr. 2009.

[68] J. Sanz, R. Perera, and C. Huerta, "Fault diagnosis of rotating machinery based on auto-associative neural networks and wavelet transforms," *J. Sound Vibration*, vol. 302, no. 4–5, pp. 981–999, May 2007.

[69] H. J. Shina, D.-H. Eomb, and S.-S. Kim, "One-class support vector machines—An application in machine fault detection and classification," *Comput. Ind. Eng.* vol. 48, no. 2, pp. 395–408, Mar. 2005.

[70] Case Western Reserve University Bearing Test Data Center. (2012, Jan.) [Online]. Available: http://www.eecs.case.edu/laboratory/bearing/

[71] Diagnostics Propulsion and Power Department, Naval Air Systems Comand (NAVAIR). (2012, Jan.) Helicopter Drivetrain Vibration Condition Monitoring Algorithms. A public domain resource sponsored by AIR 4.4.2 [Online]. Available: http://qsun.eng.ua.edu/cpw_web_new/index.htm

[72] MDTB Test-run Data CDs, Condition-based Maintenance Department, Applied Research Laboratory, The Pennsylvania State University.

[73] A. Ypma and P. Pajunen, "Rotating machine vibration analysis with second-order independent component analysis," in *Proc. 1st Int. Workshop Independent Compon. Anal. Signal Separation (ICA)*, Aussios, France, Jan. 1999, pp. 37–42.

[74] Prognostic Data Repository of the Prognostics Center of Excellence at Ames Research Center, NASA. (2012, Jan.) [Online]. Available: http://ti.arc.nasa.gov/tech/dash/pcoe/ prognostic-data-repository

[75] W. Wang and D. Kanneg, "An integrated classifier for gear system monitoring," *Mech. Syst. Signal Process.*, vol. 23, no. 4, pp. 1298–1312, May 2009.

[76] L. Zhang, R. Yan, R. X. Gao, and K. Lee, "Design of a real-time spindle health monitoring and diagnosis system based on open systems architecture," in *Proc. Int. Smart Machining Syst. Conf.*, Gaithersburg, USA, Mar. 2007, pp. 1–4.

[77] S. Cho, S. Binsaeid, and S. Asfour, "Design of multisensor fusion-based tool condition monitoring system in end milling," *Int. J. Adv. Manuf. Technol.*, vol. 46, nos. 5–8, pp. 681–694, Jan. 2010.

[78] L. Hitchcock, *ISO Standards for Condition Monitoring. Engineering Asset Management*. London: Springer, pp. 606–613, 2006.

[79] M. Lebold, K. McClintic, R. Campbell, C. Byington, and K. Maynard, "Review of vibration analysis methods for gearbox diagnostics and prognostics," in *Proc. 54th Meeting Soc. Machinery Failure Prev. Technol.*, VA, May 1–4, 2000, pp. 623–634.

[80] J. Rafiee, M. A. Rafiee, and P. W. Tse, "Application of mother wavelet functions for automatic gear and bearing fault diagnosis," *Expert Syst. Appl.*, vol. 37, no. 6, pp. 4568–4579, Jun. 2010.

[81] C. R. Farrar, T. A. Duffey, S. W. Doebling, and D. A. Nix, "A statistical pattern recognition paradigm for vibration-based structural health monitoring," *2nd Int. Workshop Str. Health Monitor.*, Stanford, CA, Sep. 8–10, 1999.

[82] N. Tandon, "A comparison of some vibration parameters for the condition monitoring of rolling element bearings," *Meas.*, vol. 12, no. 3, pp. 285–289, Jan. 1994.

[83] L. Bouillaut and M. Sidahmed, "Cyclostationary approach and bilinear approach: Comparison, applications to early diagnosis for helicopter gearbox and classification method based on hocs," *Mech. Syst. Signal Process.*, vol. 15, no. 5, pp. 923–943, Sep. 2001.

[84] S.-j. Wu, N. Gebraeel, M. A. Lawley, and Y. Yih, "A neural network integrated decision support system for condition-based optimal predictive maintenance policy," *IEEE Trans. Syst., Man Cybern. A Syst. Hum.*, vol. 37, no. 2, pp. 226–236, Mar. 2007.

[85] A. Albarbar, F. Gu, and A. D. Ball, "Diesel engine fuel injection monitoring using acoustic measurements and independent component analysis," *Meas.*, vol. 43, no. 10, pp. 1376–1386, Dec. 2010.

[86] S. Devi, L. S. Kumar, N. R. Shanker, and K. Prabakaran, "A comparative study between vibration and acoustic signals in HTC cooling pump and chilling pump," *Int. J. Eng. Technol.*, vol. 2, no. 3, pp. 273–277, Jun. 2010.

[87] A. Al Thobiani, F. Gu, and A. Ball, "The monitoring of cavitation in centrifugal pumps based on the analysis of vibro-acoustic measurements," presented at the CM 2010 MFPT 2010, U.K., Jun. 22–24, 2010.

[88] W. Wang, "An enhanced diagnostic system for gear system monitoring," *IEEE Trans. Syst., Man, Cybern. B: Cybern.*, vol. 38, no. 1, pp. 102–112, Feb. 2008.

[89] M. Todd, S. D. J. McArthur, J. R. McDonald, and S. J. Shaw, "A semiautomatic approach to deriving turbine generator diagnostic knowledge," *IEEE Trans. Syst., Man, Cybern. C, Appl. Rev.*, vol. 37, no. 5, pp. 799–992, Sep. 2007.

[90] T. Mu and A. K. Nandi, "Multiclass classification based on extended support vector data description," *IEEE Trans. Syst., Man, Cybern. B: Cybern.*, vol. 39, no. 5, pp. 1206–1216, Oct. 2009.

[91] Z. Chen, "Fault diagnosis of gear box based on information entropy," in *Proc. Control Decision Conf.*, Beijing, China, May 2010, pp. 1239–1242.

[92] P. K. Kankar, S. C. Sharma, and S. P. Harsha, "Fault diagnosis of ball bearings using machine learning methods," *Expert Syst. Appl.*, vol. 38, no. 3, pp. 1876–1886, Mar. 2011.

[93] Y. Wang, Z. He, and Y. Zi, "Enhancement of signal denoising and multiple fault signatures detecting in rotating machinery using dual-tree complex wavelet transform," *Mech. Syst. Signal Process.*, vol. 24, no. 1, pp. 119–137, Jan. 2010.

[94] P. Li, Q. He, and F. Kong, "An approach for fault diagnosis of bearings using wavelet-based fractal analysis," *Proc. IEEE Int. Conf. Inf Automation*, Harbin, China, Jun. 20–23, 2010, pp. 2338–2343.

[95] L. Fu, H. Li, and Y. Wang, "Application of bi-cepstrum analysis to gear fault detection and diagnosis," *Int. Conf. Meas. Technol. Mechatronics Automation*, China, Apr. 11–12, 2009, pp. 590–593.

[96] E. Rivas, J. C. Burgos, and J. C. García-Prada, "Vibration analysis using envelope wavelet for detecting faults in the OLTC tap selector," *IEEE Trans. Power Del.,*, vol. 25, no. 3, pp. 1629–1636, Jul. 2010.

[97] S. Delvecchio, G. D'Elia, E. Mucchi, and G. Dalpiaz, "Advanced signal processing tools for the vibratory surveillance of assembly faults in diesel engine cold tests," *J. Vibration Acoustics*, vol. 132, no. 2, Mar. 2010.

[98] J. Cheng, Y. Yang, and D. Yu, "The envelope order spectrum based on generalized demodulation time–frequency analysis and its application to gear fault diagnosis," *Mech. Syst. Signal Process.*, vol. 24, no. 2, pp. 508–521, Feb. 2010.

[99]  C. Junsheng, Y. Dejie, and Y. Yu, "The application of energy operator demodulation approach based on EMD in machinery fault diagnosis," *Mech. Syst. Signal Process.*, vol. 21, no. 2, pp. 668–677, Feb. 2007.

[100] V. Sugumaran, V. Muralidharan, and K. I. Ramachandran, "Feature selection using decision tree and classification through proximal support vector machine for fault diagnostics of roller bearing," *Mech. Syst. Signal Process.*, vol. 21, no. 2, pp. 930–942, Feb. 2007.

[101] M. Yang and V. Makis, "ARX model-based gearbox fault detection and localization under varying load conditions," *J. Sound Vibration*, vol. 329, no. 24, pp. 5209–5221, Nov. 2010.

[102] H. Wang, P. Chen, S. Fujioka, S. Wang, and K. Li, "Diagnosis method based on skewness wave and information divergence for a diesel engine," *Asia-Pacific Conf. Power Energy Eng.*, Chengdu, China, Mar. 28–31, 2010, pp. 1–4.

[103] J. Antoni and R. B. Randall, "The spectral kurtosis: Application to the vibratory surveillance and diagnostics of rotating machines," *Mech. Syst. Signal Process.*, vol. 20, no. 2, pp. 308–331, Feb. 2006.

[104] T. Barszcz and R. B. Randall, "Application of spectral kurtosis for detection of a tooth crack in the planetary gear of a wind turbine," *Mech. Syst. Signal Process.*, vol. 23, no. 4, pp. 1352–1365, May 2009.

[105] Y. Qin, S. Qin, and Y. Mao, "Research on iterated Hilbert transform and its application in mechanical fault diagnosis," *Mech. Syst. Signal Process.*, vol. 22, no. 8, pp. 1967–1980, Nov. 2008.

[106] B. Li, P.-L. Zhang, D.-S. Liu, S.-S. Mi, G.-Q. Ren, and H. Tian, "Feature extraction for rolling element bearing fault diagnosis utilizing generalized S transform and two-dimensional non-negative matrix factorization," *J. Sound Vibration*, vol. 330, no. 10, pp. 2388–2399, May 2011.

[107] R. Zhou, W. Bao, N. Li, X. Huang, and D. Yu, "Mechanical equipment fault diagnosis based on redundant second-generation wavelet packet transform," *Dig. Signal Process.*, vol. 20, no. 1, pp. 276–288, Jan. 2010.

[108] M. Li, J. Xu, J. Yang, D. Yang, and D. Wang, "Multiple manifolds analysis and its application to fault diagnosis," *Mech. Syst. Signal Process.*, vol. 23, no. 8, pp. 2500–2509, Nov. 2009.

[109] Y. Wang, Z. He, and Y. Zi, "A demodulation method based on improved local mean decomposition and its application in rub-impact fault diagnosis," *Meas. Sci. Technol.*, vol. 20, no. 2, pp. 1–10, Feb. 2009.

[110] J. Hongkai, H. Zhengja, D. Chendong, and C. Peng, "Gearbox fault diagnosis using adaptive redundant lifting scheme," *Mech. Syst. Signal Process.*, vol. 20, no. 8, pp. 1992–2006, Nov. 2006.

[111] X. Sun, "A new method of fault diagnosis with soft set theory," *Adv. Mat. Res.*, vol. 383–390, pp. 7470–7474, 2012.

[112] W. Wang, "An intelligent system for machinery condition monitoring," *IEEE Trans. Fuzzy Syst.*, vol. 16, no. 1, pp. 110–122, Feb. 2008.

**Patricia Henríquez** was born in Las Palmas de Gran Canaria, Spain. She received the M.S. degree in telecommunication engineering from the Universidad de Las Palmas de Gran Canaria (ULPGC), Las Palmas, Spain, in 2006. She is currently pursuing the Ph.D. degree at ULPGC.

Her current research interests include condition monitoring, fault diagnosis, nonlinear processing, speech processing, and pattern recognition.

**Jesús B. Alonso** received the M.S. degree in telecommunication engineering and the Ph.D. degree from the Universidad de Las Palmas de Gran Canaria (ULPGC), Las Palmas, Spain, in 2001 and 2006, respectively.

He has been an Associate Professor at ULPGC since 2002, teaching subjects on signal processing. His current research interests lie in the fields of pattern recognition, data mining, and speech recognition.

**Miguel A. Ferrer** was born in Spain in 1965. He received the M.S. degree in telecommunication engineering and Ph.D. from the Universidad Politécnica de Madrid, Madrid, Spain, in 1988 and 1994, respectively.

He is currently an Associate Professor at the Universidad de Las Palmas de Gran Canaria, Las Palmas, Spain, where he has taught since 1990. His current research interests lie in the fields of biometrics and audio quality evaluation.

Dr. Ferrer is a member of the IEEE Carnahan Conference on Security Technology Advisory Committee.

**Carlos M. Travieso** received the M.S. degree in telecommunication engineering at Polytechnic University of Catalonia (UPC), Spain, in 1997, and the Ph.D. degree at Universidad de Las Palmas de Gran Canaria (ULPGC-Spain) Las Palmas, Spain, in 2002.

He has been an Associate Professor since 2001 in ULPGC, teaching subjects on signal processing and learning theory. His current research interests include biometrics, biomedical signals, data mining, classification system, signal and image processing, and environmental intelligence.

Dr. Travieso has been a member of IASTED Technical Committee on Image Processing since 2007 and a member of IASTED Technical Committee on Artificial Intelligence and Expert Systems since 2011.