Mechanical Systems and Signal Processing 66-67 (2016) 679–698

Contents lists available at ScienceDirect

Mechanical Systems and Signal Processing

journal homepage: www.elsevier.com/locate/ymssp

Review

Spectral kurtosis for fault detection, diagnosis and prognostics of rotating machines: A review with applications

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A R T I C L E I N F O

Article history:
Received 31 January 2014
Received in revised form
25 March 2015
Accepted 5 April 2015
Available online 30 June 2015

Keywords:
Spectral kurtosis
Rotating machines
Fault diagnosis
Prognostics

A B S T R A C T

Condition-based maintenance via vibration signal processing plays an important role to reduce unscheduled machine downtime and avoid catastrophic accidents in industrial enterprises. Many machine faults, such as local defects in rotating machines, manifest themselves in the acquired vibration signals as a series of impulsive events. The spectral kurtosis (SK) technique extends the concept of kurtosis to that of a function of frequency that indicates how the impulsiveness of a signal. This work intends to review and summarize the recent research developments on the SK theories, for instance, short-time Fourier transform-based SK, kurtogram, adaptive SK and protrugram, as well as the corresponding applications in fault detection and diagnosis of the rotating machines. The potential prospects of prognostics using SK technique are also designated. Some examples have been presented to illustrate their performances. The expectation is that further research and applications of the SK technique will flourish in the future, especially in the fields of the prognostics.

Contents

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http://dx.doi.org/10.1016/j.ymssp.2015.04.039
0888-3270/

1. Introduction

Condition-based maintenance (CBM) is a maintenance program that recommends maintenance decisions based on the information collected through condition monitoring [1]. Diagnostics and prognostics are two important aspects in a CBM program. CBM plays an important role to reduce unscheduled machine downtime and avoid catastrophic accidents in industrial enterprises.

A variety of methods have been developed and summarized for rotating machinery fault diagnostics, such as vibration analysis [2], acoustic emission (AE) [3], temperature trend analysis [4] and wear debris analysis [5]. Commonly used technique for fault detection is vibration-based signature analysis. Signal processing in vibration-based monitoring of rotating machinery offers very important information about anomalies formed internally in the structure of the machinery [6]. Hundreds of papers in this field, including theory and practical applications, appear every year in academic journals, conference proceedings and technical reports. Space lacks for a detailed description of all these methods, interested readers can refer to some review works in the field of the vibration-based fault detection and diagnosis using the wavelet transform [7], multiwavelet transform [8], empirical model decomposition [9] and time–frequency analysis [10], etc. Moreover, all these fault diagnosis methods mentioned above have been used not only on the test rig of the bearings or gears, but extensively in practical equipments, such as helicopters [11], wind turbine [12–14], induction machines [15,16] and permanent magnet machines [17].

Diagnostics is conducted to investigate or analyze the cause or nature of a condition, situation or problem, whereas prognostics is concerned with calculating or predicting the future as a result of rational study and analysis of available pertinent data [18]. Prognostics has the potential to give the greatest economic benefits from the condition monitoring, but it is probably the least developed technique compared with fault detection and diagnostics methods. The information gained from vibration signal analysis enables us to plan a maintenance action [19]. Based on this analysis, the health assessment at the various stages of degradation is crucial for predicting failure and making maintenance decisions. Therefore, some methodologies in prognostics have been broadly developed based on the approaches of statistical reliability, data-driven evolutionary trend, dynamic systems, physics-based modeling, etc. Most of these methodologies and their applications in prognostics of rotary machines have been introduced in the corresponding review works [1,18,20,21].

Spectral kurtosis (SK) is one of the powerful techniques for vibration signal analysis. In recent years, SK has been paid a considerable amount of attention to the fault diagnosis of rotating machines. Knowledge of this prior works is also necessary for any future research efforts to be conducted. However, there is not a comprehensive overview that states the previous and ongoing efforts of SK. This paper thus attempts to summarize the development of SK, especially on the algorithms and their applications for fault detection, diagnosis of rotating machinery. Through the literature review, some increasing trends appear in the research field of machine prognostics using the SK technique are also discussed.

The remaining part of the paper is organized as follows. Section 2 briefly introduces the development of SK theory. Different algorithms for SK and its estimations are given in Section 3. Section 4 shows the applications of the SK in fault detection and diagnosis of the crucial parts in rotating machine, namely bearings and gears. The two prospects of SK in the prognostics using SK are presented in Section 5. Finally, Section 6 concludes the paper and provides a short list of references for applications of SK in other fields.

2. A brief history

Diagnostics and prognostics are the two important aspects of time series analysis, which individually uses signal processing and prediction technique. The higher order statistics (HOS) is an important branch of time series analysis, and has been conducted an extensive research in the past few years. Many works lead to several HOS analysis, complementary to classical second order methods. In 1983, frequency domain kurtosis (FDK) was first developed as the kurtosis of its frequency components in the frequency domain by Dwyer [22], and then it was used as a complement to the power spectral density to detect "randomly occurring signals" in [23,24]. In 1994, Pagnan and Ottonello proposed a modified definition

Nomenclature

AE	acoustic emission
AR	autoregressive
ARMPT	adaptive redundant multiwavelet packet transform
SK	adaptive spectral kurtosis
BPFO	ball passing frequency, outer race
BPFI	ball passing frequency, inner race
BSS	blind source separation
CBM	condition-based maintenance
CI	computational intelligence
CNS	conditionally nonstationary signal
CMWT	complex Morlet wavelet transform
CSA	cyclostationary analysis
DFT	discrete Fourier transform
EEMD	ensemble empirical model decomposition
EKF	extended Kalman filter
EOT	envelope order tracking
FDK	frequency domain kurtosis
FFT	fast Fourier transform
GA	genetic algorithm
HHT	Hilbert Huang transform
HOS	higher order statistics
ICA	independent component analysis
IMF	intrinsic mode function
KABS	kurtosis-based adaptive bandstop
KR	kurtosis ratio
MED	minimum entropy deconvolution
MFB	multirate filter-bank
MPDM	multiple-point defect model
OMA	operational mode analysis
PDF	probability density function
PSD	power spectral density
QAWTF	discrete quasi-analytic wavelet tight frame
REB	rolling element bearing
RUL	remaining useful life
SA	simulated annealing
SK	spectral kurtosis
SR	stochastic resonance
STFT	short time Fourier transform
SVM	support vector machine
TLSAE	tachometer-less synchronously averaged envelope
TQWT	tunable-Q wavelet transform
WPT	wavelet packet transform

based on the normalized fourth-order moment of the magnitude of short-time Fourier transform (STFT) [25,26]. They also showed that SK could be used as a filter to recover random signals even when they are severely corrupted by additive stationary noise. This conclusion actually builds the foundation for the applications of SK in the future. In 1996, a formal definition of SK via the theory of HOS was given by Capdevielle [27]. The SK was explicitly defined as the normalized fourth-order cumulant of the Fourier transform, i.e., as a slice of the tricoherence spectrum. Accordingly, SK technique can be considered as a good complementary spectral analysis tool to the traditional power spectrum density [28]. Moreover, a parallel formalization on nonstationary signals of the SK was creatively developed by means of the World-Cramer decomposition in 2004, and later a theoretical framework and properties were investigated in detail by Antoni [29]. As such, a sound definition of SK was derived from the theoretical framework, but it was no longer a slice of the tricoherence spectrum which was different from the definition in [27]. This theoretical framework is also very helpful for designing the new estimators of the SK, which is a necessary step for connecting theoretical results with the real life practice. Some improvements on the SK to the practical applications have been conducted during the next few years.

Recently, the statistical properties of the SK estimator were thoroughly investigated, and all the moments of its probability density function (PDF) were analytically determined by Gelu and Dale in [30]. It was shown that the first SK standard moments met the conditions required by a Pearson type-IV PDF [30]. In addition, the SK estimator in its original form must be developed from the instantaneous power spectral density (PSD) estimates, and thus it cannot be employed as a radio frequency interference excision tool downstream of the data pipeline in existing instruments. Gelu and Dale [31] also developed a generalized estimator with wider applicability for both instantaneous and averaged spectral data. In order to use the SK in a Gaussianity test to check whether signal points were presented as a set of STFT points, the SK of complex circular random variables as well as its relationship with the kurtosis of the real and imaginary parts were investigated in [32].

As can be seen from the development of SK, SK has become an actual research of great interest in the past decade. Its theory and different estimating methods will be introduced in detail in the following section.

3. Theoretical background of spectral kurtosis

3.1. Kurtosis

Kurtosis is a measure of peakedness, and hence it is a good indicator of signal impulsiveness in the context of fault detection for rotating components. Kurtosis is expressed as

$$kurtosis(x) = \frac{E\{(x-\mu)^4\}}{\sigma^4} - 3 \tag{1}$$

where μ and σ are the mean and standard deviation of time series x, respectively, while $E\{\cdot\}$ is the expectation operation. The “minus 3” at the end of this formula is to make the kurtosis of the normal distribution equal to zero. The kurtosis indicates the peakedness of the probability distribution associated to the instantaneous amplitudes of the time-series measurements. Kurtosis was commonly considered as an object function for fault diagnosis of rotating machinery [33–36]. As such, kurtosis-based indexes have been often used to select the proper band for the applications of envelope-based demodulation techniques. Kurtosis has also been widely applied for prognostic and condition monitoring of rolling element bearings (REBs), because it was considered as a standalone tool for a fast indication of the development of faults [37].

Based on the kurtosis in time domain, some new indexes and methodologies have been lately proposed. The envelope kurtosis (EK) [38] was a technique for selecting an optimal frequency and bandwidth window for the envelope analysis. Recently, a new scalar indicator kurtosis ratio (KR), specially designed to quantify the amount of random impulses generated by this noise, was provided to enhance vibration signals measured by laser Doppler vibrometry [39]. Indeed, the KR was a ratio of the standard kurtosis and a robust estimate of kurtosis; thus KR of the band-pass filtered signal is still related to the SK. Similarly, Wang et al. proposed an energy kurtosis demodulation (EKD) method for signal denoising and bearing fault detection in [40], based on the maximum kurtosis deconvolution technique.

3.2. Definition of the SK

To localize transients or hidden non-stationarity, Dwyer firstly applied kurtosis to the real and imaginary parts of STFT, and consequently introduced the concept of frequency domain kurtosis (FDK) in [10]. The SK was initially defined as the kurtosis of its frequency components and was compared the variability in amplitude of the different spectral frequencies. Thus, this statistical parameter indicated how the impulsiveness of a signal varies with frequency [41]. Instead, Antoni defined SK based on the Wold-Cramer decomposition which described any stochastic nonstationary process $Y(t)$ as the output of a causal, linear and time-varying system [29]:

$$Y(t)=\int_{-\infty}^{+\infty} e^{j2\pi ft}H(t,f)dX(f) \tag{2}$$

where $dX(f)$ is an orthogonal spectral process of unit variance and $H(t,f)$ is the time-varying transfer function interpreted as the complex envelope of process $Y(t)$ at frequency f. Indeed, the fundamental assumption of SK under which it applied is that the process is conditionally nonstationary (CNS). Some examples of CNS processes were introduced in [42]. It has been demonstrated that a large class of CNS processes have the fundamental property characterized by non-Gaussian PDFs [42]. The SK is then clearly expressed as the energy-normalized fourth-order spectral cumulant of a CNS process

$$SK_Y(f)=\frac{S_{4Y}(f)}{S_{4Y}^2(f)}-2,\quad f\neq 0 \tag{3}$$

where the $2n$-order spectral moments is given by

$$S_{2nY}(f)=E\left\{\left|H(t,f)dX(f)\right|^{2n}\right\}=E\left\{\left|H(t,f)\right|^{2n}\right\}\cdot S_{2nX} \tag{4}$$

Spectral cumulants of order $2n\geq 4$ have the interesting property that is non-zero for non-Gaussian processes.

Practical vibration signals are often corrupted with additive noise, thus they are CNS in nature. When $N(t)$ represents an additive stationary noise, for a CNS process $Z(t)=Y(t)+N(t)$, SK is written as

$$SK_Z(f)=\frac{K_Y(f)}{(1+\rho(f))^2}+\frac{\rho(f)^2K_N}{(1+\rho(f))^2},\quad f\neq 0 \tag{5}$$

where $\rho(f)=S_{2N}(f)/S_{2Y}(f)$ is the noise-to-signal between $N(t)$ and $Y(t)$. More specifically, when $N(t)$ is an additive stationary Gaussian noise independent of $Y(t)$, the SK of $Z(t)$ is simplified as

$$SK_Z(f)=\frac{K_Y(f)}{(1+\rho(f))^2},\quad f\neq 0 \tag{6}$$

It can be found that the basic idea behind the SK is to get a quantity that can ideally take the high values when the signal is transient, and will be zero when the signal is stationary Gaussian. Moreover, the FDK technique is presented much earlier than SK, and the comparison between them is then first given as follows.

3.3. FDK vs. SK

Frequency domain kurtosis is defined [22,24] as follows:

$$FDK_X(F_p)=\frac{E\left\{\left[X(q,F_p)\right]^4\right\}}{E\left\{\left[X(q,F_p)^2\right]^2\right\}} \tag{7}$$

in which

$$X(q,F_p)=\sqrt{\frac{h}{M}}\sum_{k=0}^{M-1}x(k,q)\cdot e^{-jkF_p} \tag{8}$$

and $x(k,q)=x[(k+(q-1)M)h], k=0, 1, \ldots, M-1, q=1,2,\ldots,n$ and $F_p=\frac{2\pi p}{M}, p=0,1,\ldots,M-1$. The $x(k,q)$ represents the discrete data and h is the interval between successive observations of the process. As such, FDK and SK are both defined as the ratio of the fourth-order moment of the STFT magnitude of a signal to the squared second-order moment of the STFT magnitude. The one important difference is that FDK is based on computing the kurtosis of the real and imaginary parts of the Fourier coefficients, whereas the SK is optimally defined for handling complex Fourier coefficients. As such, the results of FDK and SK are represented differently. In addition, SK is of great interest when the signal is cyclostationary (a special case of stationary). In the category of SK, some different approaches and implementations have recently been carried out based on filter bank estimator of the SK.

3.4. Calculation of STFT-based SK

An estimator of the SK based on the STFT was originally suggested in [22–27], while its explicit deduction from a time–frequency approach was given in [29,42,43]. For a process $Y(t)$ with an analysis window $w(n)$ of length N_w and a given temporal stepsize P, the STFT is written as

$$Y_w(kP,f)=\sum_{n=-\infty}^{\infty} Y(n)w(n-kP)e^{-j2\pi nf} \tag{9}$$

The $2n$-order empirical spectral moment of $Y_w(kP,f)$ is defined as

$$\hat{S}_{2nY}(f)=\left\langle \left|Y_w(kP,f)\right|^{2n}\right\rangle_k \tag{10}$$

with $\langle\cdot\rangle_k$ standing for the time-average operator over index k. Similar to Eq. (3), the STFT-based estimator of the SK can be defined as

$$\hat{K}_Y(f)=\frac{\hat{S}_{4Y}(f)}{\hat{S}^2_{4Y}(f)}-2, \quad |f-\mathrm{mod}(1/2)|>N_w^{-1} \tag{11}$$

Bias and variance of the estimator of STFT-based SK in detail are given in [29]. It should be mentioned that the analyzed signal should be *local stationary*, if the STFT-based estimator is unbiased. Moreover, two important conditions that the analyzed signal should meet were given in [43]. In other words, the non-stationarity of the signal should have slow temporal evolutions, as compared to the window length of the STFT. More precisely, the correlation length of the signal should be shorter than the analysis window of the STFT. However, most of the fault signals are nonstationary and are associated with the rapid impulses. Hence, this STFT-based SK estimation technique greatly depends on the window length used in the STFT.

3.5. Kurtogram and the fast kurtogram

As mentioned in Section 3.4, N_w truly affects the STFT-based SK, thus its value should be optimally selected in practical applications. The frequency f and the window length N_w could be found in maximizing the STFT-based SK over all possible choices. The map formed by the STFT-based SK as a function of f and N_w is called kurtogram [43]. Fig. 1 shows a kurtogram of a rolling element bearing signal with an outer race fault, where the global maximum is achieved for $f^*=12.5$ Hz and $N_w^*=44$ [43]. An optimal bandpass filter for the envelope analysis was determined from the maximum of the SK with optimal N_w^*. Thus, the optimal central frequency f_c and bandwidth of the band-pass filter B_f can be determined with which jointly maximize the kurtogram.

To yield the “true” center frequency and bandwidth, all possible window widths should be enumerated, which is computationally expensive and may not be realistic in real applications. Based on the multirate filter-bank structure (MFB) and quasi-analytic filters, the fast kurtogram was further developed to fast compute and figure out the results of SK by Antoni in [44]. The results of the fast kurtogram are very similar to those of kurtogram, which can be seen in Fig. 9 in [44]. The fast kurtogram can be computed more quickly than the kurtogram, thus it has been widely used and almost considered as a benchmark technique for mechanical fault diagnosis. Without confusion, we simply use kurtogram to represent the fast kurtogram in the following work.

The principle of the kurtogram algorithm is based on an arborescent MFB structure. A 1/2-binary tree kurtogram estimator is shown in Fig. 2, where center frequency and bandwidth can be automatically determined. Those colors shown in different squares in Fig. 2 clearly indicate the values of SK. Therefore, the maximum value can be easily found by some simple searching technique.

3.6. Adaptive SK

The purpose of the adaptive SK (ASK) method is to determine the center frequency and bandwidth (window length) via a simple greedy approach. ASK is implemented by right-expanding a given window along the frequency axis through successive attempts to merge it with its subsequent neighboring windows and thus finally maximizing the SK value.

The ASK technique successively attempts to right-expand a given window along the frequency axis. Therefore, the original signal is first transformed to the frequency domain:

$$\hat{x}[n] = \sum_{k=0}^{N-1} x[k] e^{-i\frac{2\pi}{N}kn} \tag{12}$$

where $\hat{x}[\cdot]$ is the Fourier sequence of the signal and N is the length of the signal. The windowed signals in frequency domain based on the current window $w_r^{r_i}$ and its translated version $T_{la}w$ are respectively written as

$$\hat{x}_{w_r}^{r_i}[n] = \hat{x}[n] w_r^{r_i}[n] = \sum_{\tau=r_i}^{r_i+r} \hat{x}[n] w[n-\tau a] \tag{13}$$

$$\hat{x}_{T_l w}^{r_i}[n] = \hat{x}[n] \cdot T_{la} w[n] = \hat{x}[n] w[n-la] \tag{14}$$

where $l = r_i + r + 1$. Similarly, the windowed signal based on the superposition of $w_r^{r_i}$ and $T_{la}w$ windows is

$$\hat{x}_{w_l}^{r_i}[n] = \hat{x}[n] w_l^{r_i}[n] = \sum_{\tau=r_i}^{l} \hat{x}[n] w[n-\tau a] \tag{15}$$

Then, filtered signals can be obtained by inverse FFT , i.e.,

$$x_{w_\zeta}^{r_i}[k] = \frac{1}{N \cdot G(\lambda, r)} \sum_{n=0}^{N-1} \hat{x}_{w_\zeta}^{r_i}[n] e^{i\frac{2\pi}{N}nk} \tag{16}$$

where w_ζ indexes w_r,w_{T_l} and w_l,λ is the overlap ratio, and $G(\lambda, r)$ is the gain of the filter resulting from the superposed window. The estimate of $G(\lambda, r)$ and the performance of different local window function superposition are given in [45].

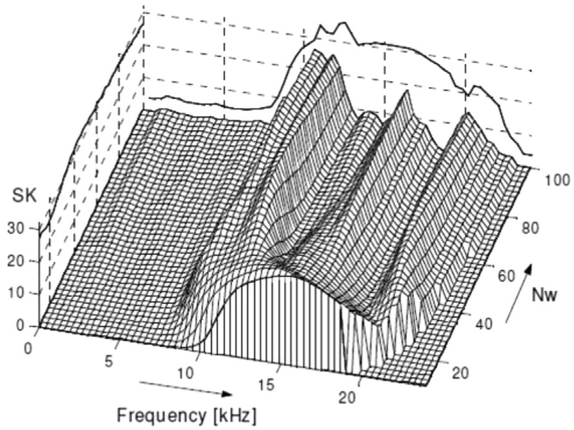

Fig.1. SK computed with different N_w and f (Fig. 13 in [44]).

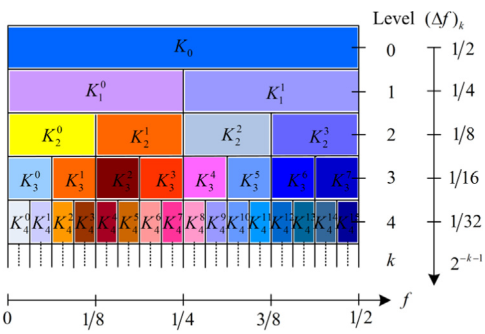

Fig. 2. Combinations of center frequency and bandwidth for the 1/2-binary tree kurtogram estimator .

The kurtosis of the filtered signals using window w_r,w_{T_l} or w_l as a bandpass filter can be computed by

$$\kappa_{r_i}\left[x_{w_\zeta}\right]=\frac{\sum_{k=0}^{N-1}\left|x_{w_\zeta}^{r_i}[k]-\left\langle x_{w_\zeta}^{r_i}\right\rangle\right|^4}{\left(\sum_{k=0}^{N-1}\left|x_{w_\zeta}^{r_i}[k]-\left\langle x_{w_\zeta}^{r_i}\right\rangle\right|^2\right)^2}-2 \tag{17}$$

where w_ζ indexes w_r,w_{T_l} and w_l,$\langle\cdot\rangle$ is mean operator, $\kappa_{r_i}[\cdot]$ is the r_ith adaptive windowed SK, and constant "-2" comes from the fact that $x_{w_\zeta}^{r_i}[k]$ is complex. As can be seen in Eq. 17, kurtosis is practically derived from a temporal signal $x_{w_\zeta}^{r_i}$. However, signal $x_{w_\zeta}^{r_i}$ results from a frequency window, and thus the kurtosis corresponding to the frequency domain can be also obtained. That is why the ASK technique is named as adaptive SK. The process of merge is accepted only if it leads to higher or equal spectra kurtosis, i.e.,

$$\kappa_{r_i}[x_{w_l}] \geq \max\{\kappa_{r_i}[x_{w_r}],\kappa_{r_i}[x_{w_{T_l}}]\} \tag{18}$$

where subscripts w_r, w_{T_l} and w_l represent the current window, the immediate translated neighboring window, and the merged window, respectively. If the above condition is not satisfied, an attempt will be made to merge the next window with its immediate right-translated window. This process repeats until all windows have been tested for merging. Fig. 3 represents the above mentioned window merging process, where each dot (—o—) in Fig. 3 stands for the SK value derived from an initial window. Actually, Fig. 3 also shows the adaptive paving of the time-frequency plane using the window merging.

Provided that the initial width of window w is M, the central frequency and bandwidth deduced from the windowed data $\hat{x}_{w_r}^{r_i}$ are mostly located in $[r_i a,(r+r_i)a+M/2]$. For more details about the ASK technique, interested readers should refer to Ref. [46].

The comparison between the ASK and the STFT-based SK are given in Fig. 4. As can be seen in Fig. 4(a), different window lengths resulted in different results (center frequency and bandwidth) when the STFT-based SK method is applied. Nevertheless, the optimal filter parameters could be determined without enumerating all possible window lengths by using the ASK method, as is depicted in Fig. 4(b).

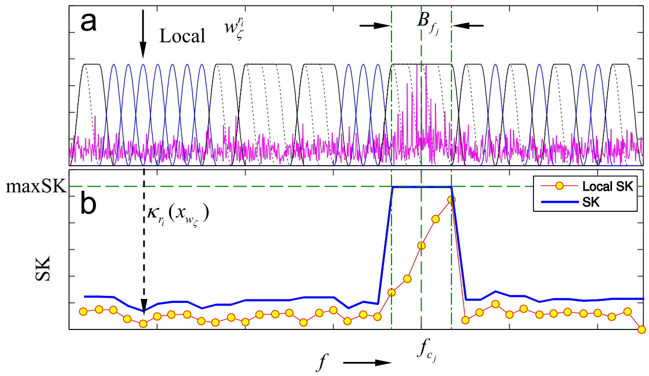

Fig. 3. The adaptive windowed SK technique and the obtained optimal filter.

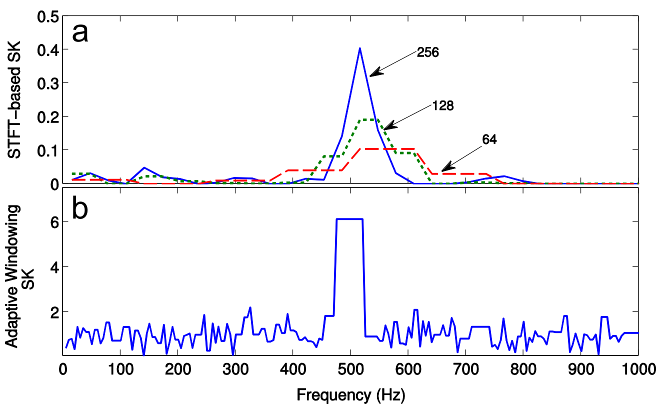

Fig. 4. The STFT-based SK and the proposed adaptive SK (Fig. 3 in [46]).

3.7. The protrugram

Protrugram was proposed based on the kurtosis of the envelope spectrum amplitudes of the narrowband envelope signals calculated in the frequency domain via Hilbert transform in [47], which is different from on the computation of the kurtosis of the filtered time signal. However, this practice did not give theoretical justification. Actually, the protrugram can be considered as the special case of the ASK and more details can be seen in the work [46]. Because protrugram is computed based on the envelope spectrum of x_{na}, i.e. $\check{x}_{w_{na}} = F(|x_{w_{na}} + jH(x_{w_{na}})|)$, where $H(\cdot)$ is the Hilbert transform operator, $F(\cdot)$ is the Fourier transform operator and $|\cdot|$ is the modulus of the signal. It can be written in theory as follows

$$\check{\kappa}_n\left[x_{w_{na}}\right] = \frac{\sum_{k=0}^{N-1}\left|\check{x}_{w_{na}}[k] - \langle \check{x}_{w_{na}} \rangle\right|^4}{\left(\sum_{k=0}^{N-1}\left|\check{x}_{w_{na}}[k] - \langle \check{x}_{w_{na}} \rangle\right|^2\right)^2} - 2, \quad n = 0, 1, 2, \ldots, \left\lfloor \frac{F_s - M}{2a} \right\rfloor \tag{19}$$

The calculation of the protrugram requires the additional parameter – the size of the step of scanning, i.e., how much the central frequency is shifted on the frequency axis after each iteration. Fig. 5 shows three protrugrams for constant BW with variable step size.

In short, several different approaches have been investigated to measure the kurtosis of a signal as a function of frequency. Results of SK technique in nature are the output of a series of bandpass filters covering a wide frequency range. Vibration signals are known to be highly nonstationary, especially when a fault occurs in a rotating machine, which will provoke a series of impacts. SK technique is very powerful in detecting those impulsive signatures from signals even buried with great noises. The applications of SK in the fields of fault detection, diagnosis of rotating machines are given in the next section, where some improvements on the SK are mentioned as well. The thorough comparisons among the diverse SK approaches are beyond the scope of this work; however, the comparisons among the kurtogram, ASK and protrugram in identifying the multiple signatures of bearings are given in [48].

4. Applications of SK in rotating machine fault diagnosis

It is desirable to derive the signatures of interest from vibration signals picked up around the machine components with localized faults, such as REBs and gears. Hence, these applications of SK are mainly illustrated in the following two aspects.

4.1. Applications in detecting bearing faults

REBs are the common components in rotating machinery, and thus they have received great attention in the fields of condition monitoring. Signals resulted from the localized faults in bearings are impulsive, at least at the source, thus SK has been mostly utilized to identify the frequency bands in which this impulsivity is most marked [49]. For instance, SK was

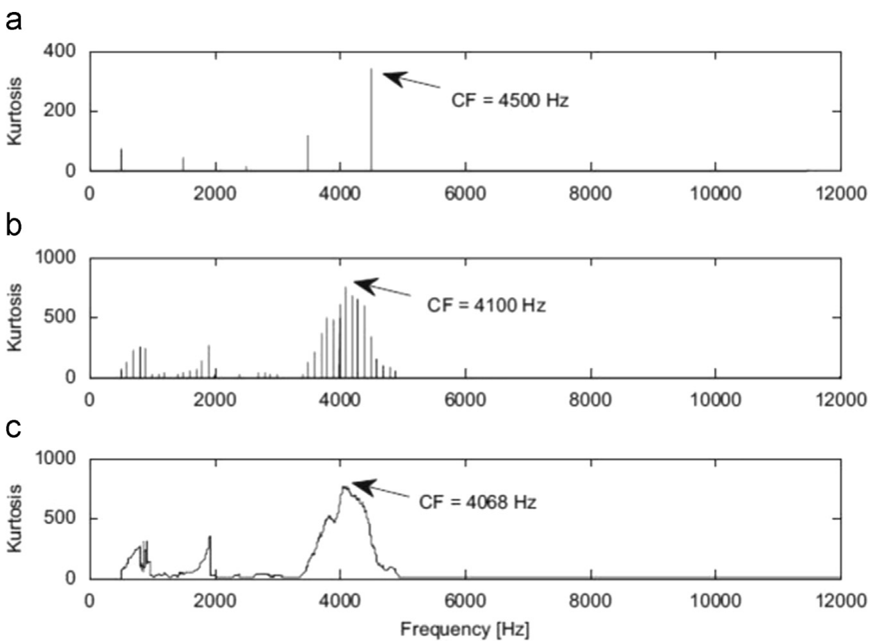

Fig. 5. Protrugrams for constant BW = 500 Hz and varying stepsize: (a) 1 kHz, (b) 100 Hz and (c) 1 Hz (Fig. 11 in [48]).

directly applied to the REB fault detection in an asynchronous machine in [50]. Professor Randall systematically introduced the applications of SK in machine diagnostics and he also early gave some trends for SK in the fields of prognostics [51]. The kurtogram has now also been used for feature extraction of gear/bearing dynamic model in the presence of bearing faults [52], as well as real-time automatic detection of REB fault in induction machine [53].

4.1.1. Improvements on the time–frequency frame used in the SK

Many signal time–frequency decomposition methods have ever been adopted to perform the different multirate filter-bank structures used in the SK technique. Complex Morlet wavelet transform (CMWT) was applied as a filter bank with

Table 1
Different time–frequency decomposition methods used in the improved SK techniques.

Time-frequency Decomposition method	SK technique	References	Comments
CMWT	STFT-based SK	[54,56]	Uniform resolution on a logarithmic frequency scale
WPT	Kurtogram	[57,75]	More dedicated division of the time–frequency plane
Adaptive superposition widows in frequency domain	ASK	[46]	Adaptive time-frequency decomposition
ARMPT	Kurtogram	[58]	Adaptive construction of multiwavelet using two-scale similarity transform
TQWT	Similar to ASK	[59]	More flexible for the Q-factor of the WT
QAWTF	Kurtogram	[60]	Quasi-analytic wavelet tight frame as the detection filters
KABS	ASK	[34]	Remove sinusoidal interferences
Multiwavelet transform	Kurtogram	[62]	Customized construction of Multiwavelet
Morlet wavelet	ASK	[55]	Morlet wavelet used as filter bank and center frequency defined by wavelet correlation filtering

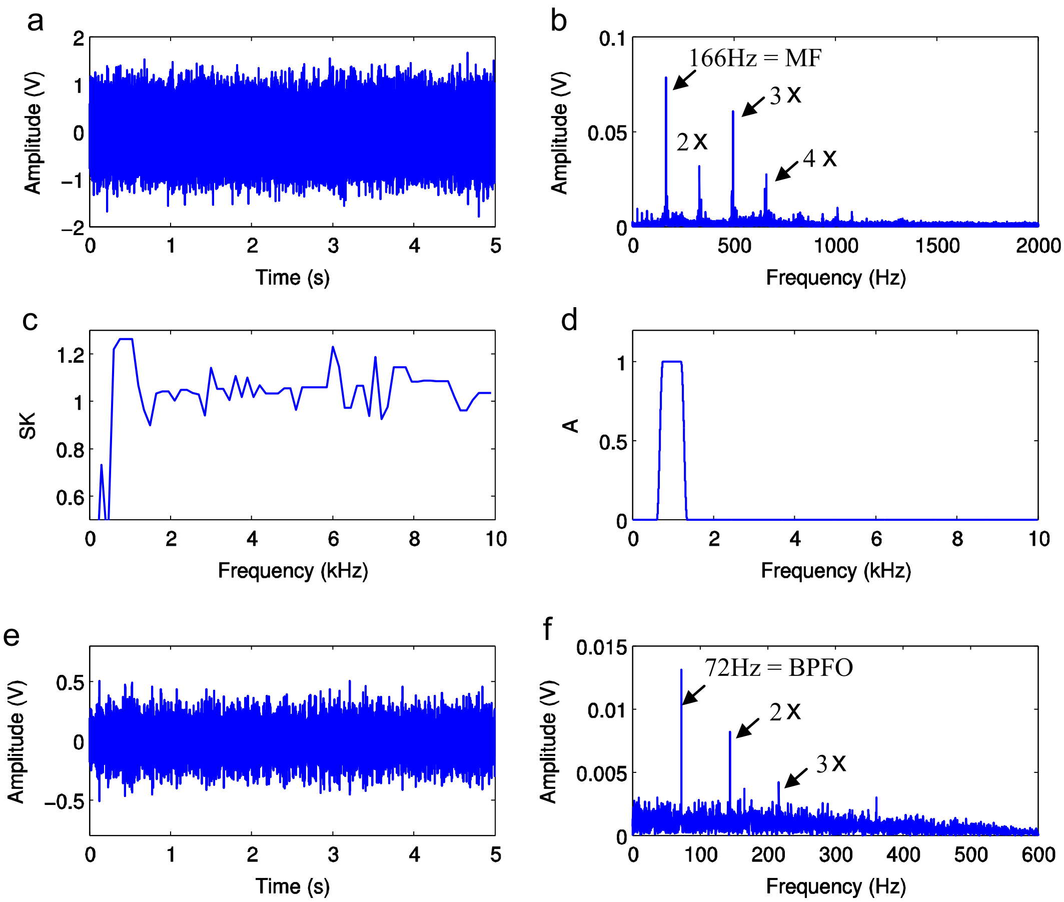

Fig. 6. The case for bearing fault detection with ASK. (a) Original signal collected from bearing interaction with gear; (b) its spectrum; (c) the SK using ASK; (d) the optimal filter resulted from the ASK method; (e) the filtered signal; (f) the Fourier spectrum of the signal envelope in (e).

uniform resolution on a logarithmic frequency bandwidth in [54]. Liu et al. developed an adaptive kurtosis filtering technique based on Morlet wavelet, in which Morlet transform was used a filter bank [55]. For the envelope analysis, different banks were applied to select the best filter that maximized the SK. Envelope analysis of the wavelet-filter based SK was mentioned for bearing health monitoring [56]. An improved kurtogram based on the wavelet packet transform (WPT) was developed for extracting fault characteristics of REBs in [57]. Recently, some newly developed wavelet transforms have been adopted in the SK technique, such as an adaptive redundant multiwavelet packet transform (ARMPT) was introduced into the SK, and it was then applied to the fault detection of REB and gear [58]. A kurtosis-guided adaptive demodulation technique for bearing fault detection based on tunable-Q wavelet transform (TQWT) was given in [59]. Discrete quasi-analytic wavelet tight frame (QAWTF) expansion methods were incorporated as the detection filters used in SK [60]. Since the QAWTF is constructed based on dual tree complex wavelet transform, the vibration transient signature extracting ability of SK technique is further improved compared with other wavelet transform [61]. In addition, a bearing fault detection method based on kurtosis-based adaptive bandstop filtering (KABS) and iterative autocorrelation was developed in [34]. The multiwavelet transform based on lifting scheme was used as the filters used in SK and multiwavelet SK was then applied for rolling bearing fault diagnosis [62]. All those mentioned different time-frequency decomposition methods along with the used SK techniques are summarized in Table 1. It is worth noting that adaptive superposition widows derived by using ASK can be considered as an improved time–frequency decomposition for SK technique, for ASK is inspired by adaptive time-frequency analysis method [63].

Gears and bearings are always two inseparable parts in most of rotating machines in the industry today. It is still very challenging for fault diagnosis of a rotating machine due to the contemporary presences of more than one cyclostationary source and additive noise in the acquired vibration signal, for example, signals acquired in a gearbox. Here, an example is given below to detect bearing outer-race fault using ASK. We want to use this case to show the effectiveness of ASK on detecting bearing fault under the influence of gears. The vibration signal was sampled at 20,000 samples/s and the shaft speed was set at 1422 RPM (f_r=23.7 Hz) leading to bearing fault characteristic frequency 72 Hz (BPFO =3.052f_r). The original signal and its corresponding spectrum are given in Fig. 6(a) and (b), respectively. As can be seen in Fig. 6(b), the spectrum of the measured signal is dominated by frequency components associated with the gearbox meshing frequency (MF=166.3 Hz) and its harmonics. The SK values and the corresponding optimal filter derived by using ASK are shown in Fig. 6(c) and (d). Based on the optimal band-pass filter, the filtered signal and its envelope spectrum are illustrated in Fig. 6 (e) and (f). As can be easily seen in (f), the outer race fault characteristic frequency and several of its harmonics can be clearly detected from envelope spectrum.

4.1.2. *Combinations with other methods for bearing fault detection*

In the early introduction of SK, it was exploited in bearing fault detection individually, without using other methods. Nevertheless, the combination of SK with other techniques has recently attracted much more attention. SK is very useful as a filter function to filter out that part of the signal with the highest level of impulsiveness [49], as such SK can be also used as a preprocessing for other techniques. In addition, the SK technique can be enhanced by some preprocessing technique, such as, an autoregressive (AR) model as a prewhitening [51]. A hybrid signal processing method that combines SK with ensemble empirical mode decomposition (EEMD) was developed to diagnose the status of bearings through vibration signal analysis [64]. A procedure combining the customary HHT with kurtogram was developed to extract high-frequency features from several kinds of faulty signals, where the kurtogram was applied to locate the nonstationary intra- and inter-wave modulation components in the original signals and produced more monochromatic intrinsic mode functions (IMFs) [65]. Based on segmentation thresholds by autocorrelation analysis of WPT coefficients, a noise reduction method was proposed for bearing early fault diagnosis combined with SK [66]. Rotating machinery vibration analysis involves a convolute mixture due to the propagation medium and environmental disturbances. A fault feature extracting method for rotating machinery vibration was given in [67], based on SK and blind deconvolution techniques. An algorithm for enhancing the surveillance capability of SK in rolling element bearings by using the minimum entropy deconvolution (MED) technique [68]. The MED technique is one of the blind deconvolution techniques and can well deconvolve the effect of the transmission path and clarifies the impulses. Vibration signals collected from bearings often corrupted with gear signals which are usually represented as modulated sinusoidal components. Based on the optimized SK for initializing series of extended Kalman filters (EKF), an automatic method for removing modulated sinusoidal components in signals was developed in [69]. It should be mentioned this application in [69] is different from the others, because SK was used to track and remove sinusoidal components rather than to detect impulsive features from signals. By applying both cyclostationary analysis (CSA) and SK for the selection of a frequency band in which variations in vibration patterns are most expressed, improperly lubricated bearings from vibration patterns can be successfully detected when records from short operating periods are available [70]. Based on the kurtogram and the parameter of the non-Gaussian alpha-stable model, a method for bearing fault detection was given in [71]. An envelope order tracking (EOT) analysis scheme was proposed for the fault detection of rolling element bearing under varying-speed running condition in [72], where the kurtogram algorithm was utilized to obtain both optimal center frequency and bandwidth of the band-pass filter. By means of the determination of the center frequency and bandwidths, a system defined by the Duffing equation in the presence of defective bearing signal was developed in [73], where the state changes of the rolling element bearing can be identified using the phase plane trajectories and Lyapunov exponents of Duffing equation. SK combined with AR model was applied to the fault diagnosis and condition monitoring of bearings [74]. An enhanced kurtogram was proposed to determine the resonance frequency

Table 2
Major methods combined with a SK technique for bearing fault detection.

Technique	SK technique	References	Comments
AR model	STFT-based SK	[51,74]	Filtering of the residual signal
EEMD	STFT-based SK	[64]	SK used as optimal band-pass filter (preprocessing)
Blind deconvolution	Kurtogram	[67]	SK posterior to BS (postprocessing)
MED	CMWT-based SK	[68]	MED prior to SK and sharpens impulses
EKF	Optimized SK	[69]	Optimized SK for initializing series of EKF
CSA	CMWT-based SK	[70]	SK for the selection of a frequency band
Alpha-stable model	Kurtogram	[71]	Kurtogram was generated using α parameter
EOT	Kurtogram	[72]	Kurtogram was used as preprocessing to determine signatures
Duffing equation	STFT-based SK	[73,74]	For selection of central frequency and bandwidth using SK
GA	Kurtogram	[76]	SK for initial estimates and GA for final optimization
SA	Kurtogram	[77]	Kurtogram was used to yield a starting point and SA was used to maximize the SK

bands in [75], where kurtosis values calculated based on the power spectrum of the envelope of the signals extracted from wavelet packet nodes at different depths. In the enhanced kurtogram technique, the sparse representation of the signals was defined by the power spectrum of the envelope of the signals, whose sparseness was measured by kurtosis. This technique can be further considered as an improvement on the protrugram.

Moreover, in order to determine an optimal band-pass filter parameters (i.e., center frequency and bandwidth), some optimization techniques were applied to select the filter parameters given by SK, for instance, genetic algorithm (GA) was used to select an optimal band-pass filter parameters for diagnosis of rolling element bearings based on the fast kurtogram [76]. A method based on simulated annealing (SA) was developed to locate the optimal frequency band in fast kurtogram [77]. This technique modeled SK as a function of the variables of a band-pass filter; the central frequency and the bandwidth were optimized by maximizing SK through SA [77]. It should be mentioned that optimal technique has also been incorporated into ASK, because the ASK adopted greedy algorithm for the window merge decision. Most of these methods for bearing fault detection are summarized in Table 2, where the combination with a SK technique can be clearly found.

Since kurtogram is very powerful to detect impulses, it has been considered as a benchmark for bearing fault diagnosis. The source code of the kurtogram is available at Antoni's personal webpage,[1] thus it is often conducted as a competitor when other new technique is proposed. For example, in Ref. [61], a multiple feature detection technique for bearings was proposed based on dual-tree complex wavelet transform (QTCWT), and it was compared with kurtogram. Similarly, a weak signal detection method was provided based on stochastic resonance (SR) [78]. Compared with the SK technique in detecting bearing fault characteristics, some other techniques are presented in Section 4.1.4.

4.1.3. Multiple bearing faults detection

Because multiple bearing faults may co-exist in reality, diagnosis of defects on multiple parts of the bearing may be necessary via vibration monitoring analysis. However, simultaneous detection of multiple transient signatures is still a big challenge for monitoring and diagnosis of rotating machinery, thus only a few of works have been reported in the fields. A multiple-point defect model (MPDM) that characterizes the dynamics of n-point bearing defects was proposed in [79]. MPDM was further extended to model degradation in a rotating machine as a special case of multiple-point defects. The dual-tree complex wavelet transform was one of the few techniques applied to extract the multiple fault signatures in a rotating machine [61]. Blind source separation (BSS) was used to recover the unknown independent sources from the observed signals mixed with an unknown propagation medium in [80]. Independent component analysis (ICA) has ever been used to separate features from a one-dimensional signal [81]. In addition, some classification techniques are also adopted to identify the compound bearing fault, as those were given in [82,83]. Recently, two new techniques were proposed for the multi-fault diagnosis based on multiwavelet packet transform [84,85].

An example in detecting multiple bearing faults using kurtogram and ASK are given here. Based on the ASK and kurtogram, the results of vibration signal acquired for bearings with different defect, namely, the inner race defect and outer race defect, are shown in Fig. 7(a) and (b). Based on the maximum, two filtered signals and their envelope spectra are given in Fig. 7(c)–(f), in which the associated BPFO and BPFI are respectively shown at 72.08 Hz and 109.6 Hz.

4.1.4. Comparisons with other techniques for bearing fault detection

The performances of SK and envelope kurtosis as a technique for setting the window with the optimal center frequency and bandwidth for the envelope analysis were quantified in [38]. A fault detection procedure was presented for bearing damage based on the statistical analysis of vibration and current signals [86,87]. Kurtogram was only used to identify the bandwidth, where the effect of the fault was stronger and the energy of the signal in this bandwidth was used as a diagnostic index [87]. SK for frequency band selection in bearing diagnostics was compared with SVM in [88], in which these two totally different approaches came to the similar conclusions.

[1] http://www.utc.fr/∼antoni/fast.htm

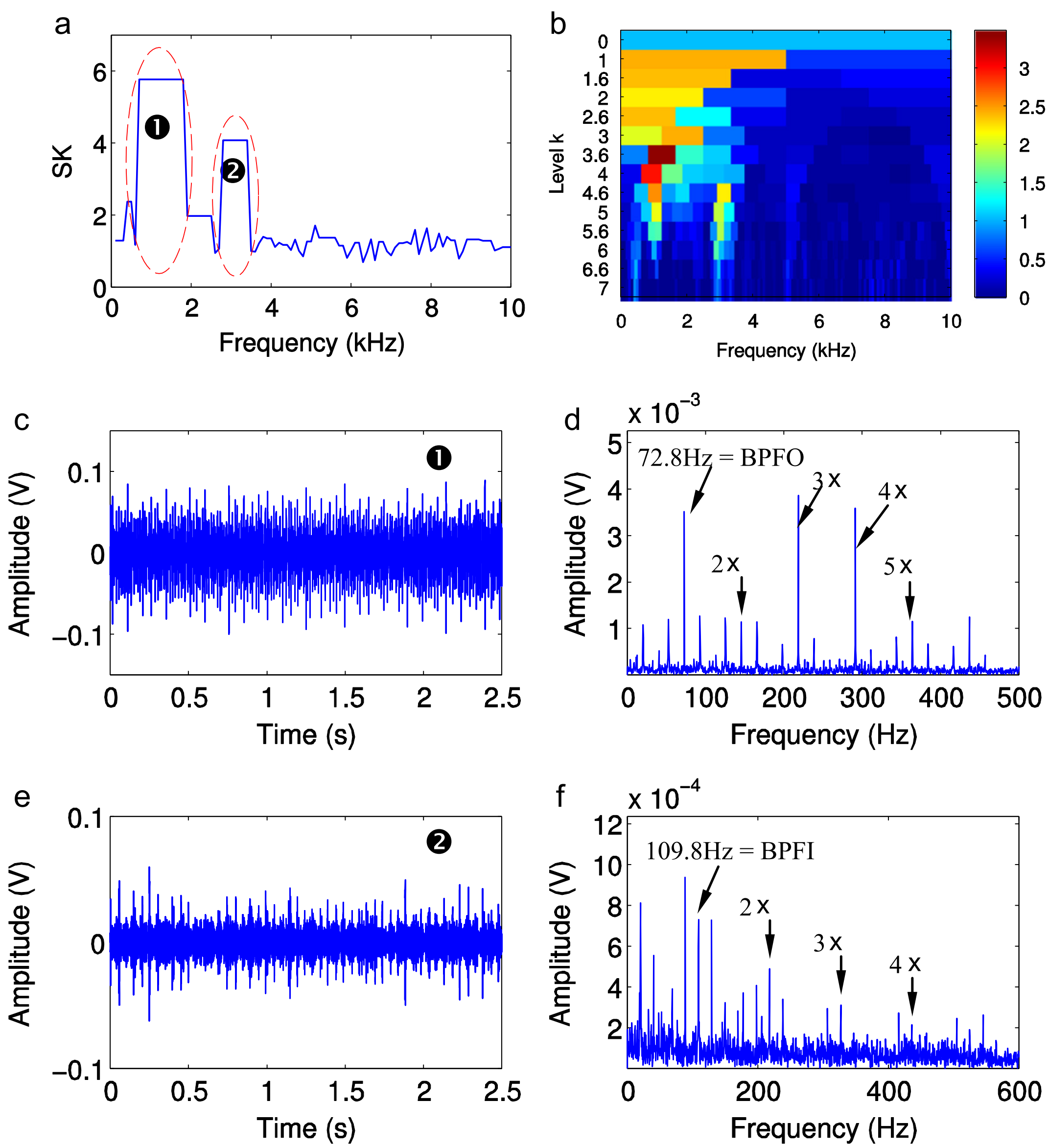

Fig. 7. A case for detecting multiple bearing fault with ASK. (a) The SK of signal collected from bearings with multiple faults using the ASK technique Temporal signal. (b) Result of SK using kurtogram. (c) and (d) The detected temporal signal with two different optimal filters according to SK in ❶ and ❷; (e) and (f) their envelope spectra.

An investigation that compared the applicability of acoustic emission (AE) and vibration technologies in monitoring a naturally degraded roller bearing was provided in [89], which attempted to investigate the comparative effectiveness of applying the kurtogram to both vibration and AE data from a defective bearing. Experimental comparison between diagnostic indicators for bearing fault detection in synchronous machine by SK and energy analysis was provided in [90], and it also demonstrated the SK-based indicators achieved a better discrimination between healthy and faulty bearing cases.

4.2. Detection of tooth faults in gearboxes

Gearbox is another important part in a rotating machine. Though some methods have been developed for diagnosis of the gearbox using SK technique, for instance, an optimal denoising filter to enhance small transients in gear vibration signals [91], the fault diagnosis of a gearbox is much more difficult than that of a bearing. From the SK-based filtered residual signal, the local power was defined as the smoothed squared envelope. The methodology is then applied to an industrial case and shows the possibility of detection of relatively small tooth surface pitting in a two-stage helical reduction gearbox. The application of the SK technique for detection of a tooth crack in the planetary gearbox of a wind turbine was presented in [92]. Based on kurtogram and band pass filter tuning with a combination of one-dimensional and multi-dimensional search schemes, a real time feature extraction approach for detecting of gear fault was presented in [93]. Recently, maximum correlated kurtosis deconvolution method [94] was applied to gear tooth chip fault detection. Sparsity-enabled signal decomposition using TQWT for fault feature extraction of gearbox was proposed in [95], which was also compared with the SK technique. A construction of lifting-based adaptive multiwavelets with various moments for fault diagnosis of rolling bearing and gearbox was presented in [96], and comparisons for the proposed method with the SK on all the applications

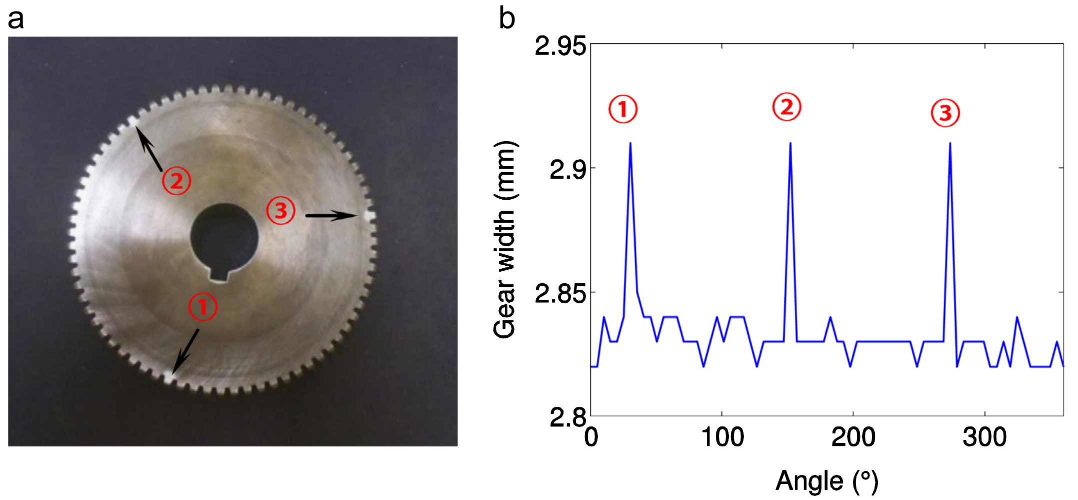

Fig. 8. The spur gear with deviation of the profile of the flank and its measured tooth width.

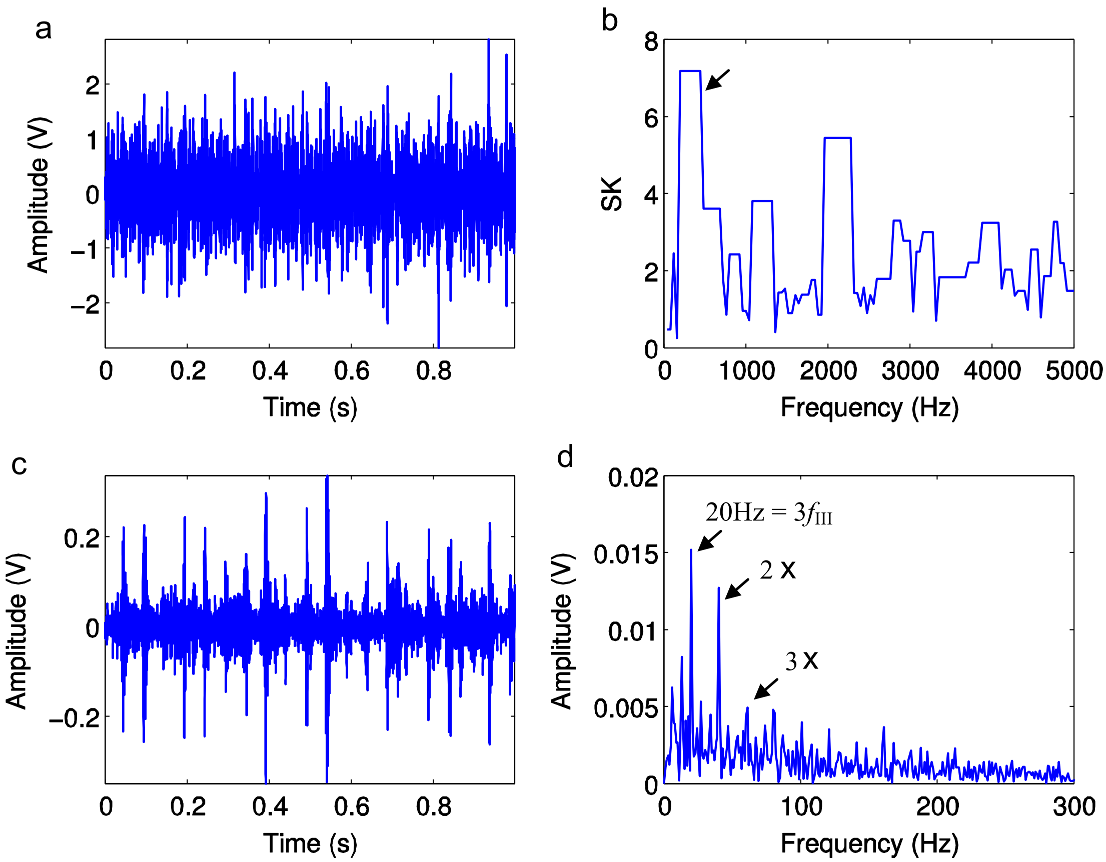

Fig. 9. The case for gear fault detection with ASK. (a) Original signal collected from gearbox (b) its SK; (c) the optimal filter resulted from the ASK method; (d) the Fourier spectrum of the signal envelope in (c).

were given as well. We can easily find the applications of SK technique in the fields of diagnosis of gearbox are still very rare.

A case of the fault detection of gear tooth based on ASK is given in this section. The signal was collected from a two-stage spur parallel gearbox. The input shaft frequency f_I was set to 30.19 Hz, while the output shaft frequency f_{III} was 6.71 Hz $\left(=\frac{z_1 z_3}{z_2 z_4} f_I = \frac{80 \cdot 72}{32 \cdot 40} f_I\right)$. The profile of the flank of the spur gear on the output shaft has some deviation due to the manufacturing error. The spur gear and its measured width are shown in Fig. 8. We can find three big teeth circumferentially distributed at equal intervals. As such, the pinion teeth will mesh with the "big tooth" three times on the gear when the gear rotates one period. The original signal is illustrated in Fig. 9(a). The derived SK using ASK technique is shown in Fig. 9(b), in which the optimal filter can be deduced from the maximum of SK. Therefore, the band-pass filtered component and its envelope spectrum are separately depicted in Fig. 9(c) and (d). In the filtered temporal signal, we can easily see that there are many periodically impacts resulting from the deviation of the gear's flank. The frequency of these impacts is about 20 Hz ($=3f_{III}$), which well demonstrates the defect of the gear.

4.3. Discussion

The applications of SK on the bearings and gears have been separately reviewed in the previous subsections. Since the literature on this subject is huge and diverse, a review on all of the literature is impossible, and omission of some papers would be inevitable. We can conclude that SK is mostly used to generate filters to extract the most impulsive part of the signal from background noise or other interactions. In general, to use kurtosis as a diagnostic tool can be also summarized according to the following categories: kurtosis of a filtered temporal signal [33,34,36,37,59,69]; spectral kurtosis as a tool for selection of frequency band for demodulation [42–44,46–48,53,57,58,64,65,71–73,75,76,87,91–93,97,98]; filtration of residual signals [68,74,91,94] and transient event detection [41,60,99–102] as well as harmonic component detection [103]. Moreover, pre-whiten the signal using some techniques, for instance, an AR model technique can further enhance the impulsiveness.

As is well known, narrowband amplitude demodulation is a common method for the fault detection of the rotating machine, but it needs extra frequency band information. Compared with the classical approach to the non-stationary signal analysis, it is shown that SK can automatically indicate the optimum frequency at which to perform amplitude envelope demodulation to obtain an envelope signal without requiring historical data or a priori knowledge. It should be also highlighted that the purpose of all kinds of SK techniques for bearing fault detection can be considered as the tools for optimum frequency band selection for the envelope analysis. It is no doubt that many other techniques can be used to do this work, spectral coherence density [104], Jarqe–Bera statistic-based selector [105], sparsogram [106] and modulation intensity distribution [107], to name only a few.

Time–frequency analysis is a very popular technique for the analysis of the mechanical signal and fault diagnosis, among which, Wigner–Ville distribution, wavelet transform, empirical mode decomposition and their diverse improved versions have been frequently adopted in recent years. Interested readers refer to the corresponding works [7–10,108], in which the developments of these methods were reviewed in detail. When these time-frequency analysis methods are used in fault detection, the meaningful components should be empirically selected for the following envelope analysis. That is one disadvantage of time–frequency analysis compared with SK. Nevertheless, time–frequency analysis can be used for the feature extraction of the non-stationary signals, such as those signals acquired during the runup or rundown experiments of a machine, while SK is not suitable to analyze these signal due to the limitation of fundamental assumption in theory. Actually, time-frequency decomposition method has been embedded in the SK technique to calculate the kurtosis for each frequency line, as is mentioned in the Section 4.1.1. Thus, the further research on the time–frequency algorithms will pave the way for the development of SK.

5. Prospects of SK in prognostics of rotating machine

Vibration monitoring and analysis in rotating machinery, on the one hand, offers very important information about anomalies of the machinery; on the other hand, enables to plan the prognostics. Prognostics addresses the use of automated methods to analyze the degradation of physical system performance and calculate the remaining life in acceptable operating state before failure or unacceptable degradation of performance occurs [21]. These two aspects of prognostics are introduced as follows.

5.1. Degradation analysis for run-to-failure testing

The major role of degradation analysis is to investigate the evolution of physical characteristics or performance measures of a crucial component leading up to its failure. Selecting a proper feature space that can reflect the comprehensive performance degradation is very important. Pervious researches have shown that different features are sensitive to different faults and degradation stages, for example, kurtosis value, crest factor and impulse factor are very sensitive to impulse faults, especially in their incipient stage, but these features will decrease to normal-like levels as the damage grows. Hence, Lybeck [109] studied the correlation of some statistic features with spall length, including RMS, kurtosis, signal peakedness, crest factor and some higher order statistics, while results showed that none of them is sensitive or consistent enough to be used as a sole indicator of spall size. Moreover, some computational intelligence (CI) approaches have been exploited in the process of prognostics. For example, a monotonic degradation assessment index of rolling bearings using fuzzy support vector data description and damage severity index was given in [110]. In [111], an incremental rough support vector data description was designed based on the rough support vector description, and a new assessment indicator was also proposed. In [112], a method of prognostics for machine condition was proposed using energy based monitoring index combined with CI. Based on lifting wavelet packet decomposition and fuzzy c-means, a bearing performance degradation assessment was proposed in [113]. A dynamic degradation observer [114] for the identification and assessment of bearing degradation was proposed based on the Mahalanobis–Taguchi system and self-organization mapping network. Most of the above mentioned techniques required the rotating speed information, thus a tachometer-less synchronously averaged envelope (TLSAE) feature extraction technique was proposed recently for rolling element bearing health assessment [115]. In the case of

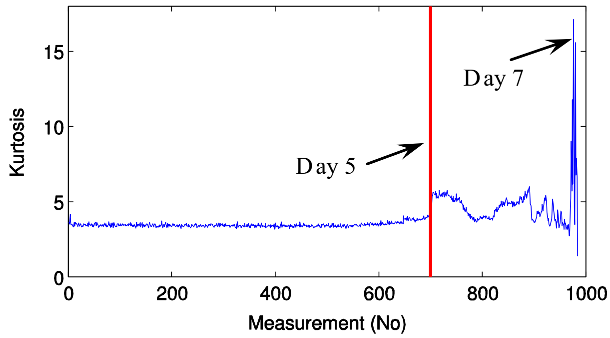

Fig. 10. Kurtosis of measurements on a bearing submitted to an accelerated fatigue test.

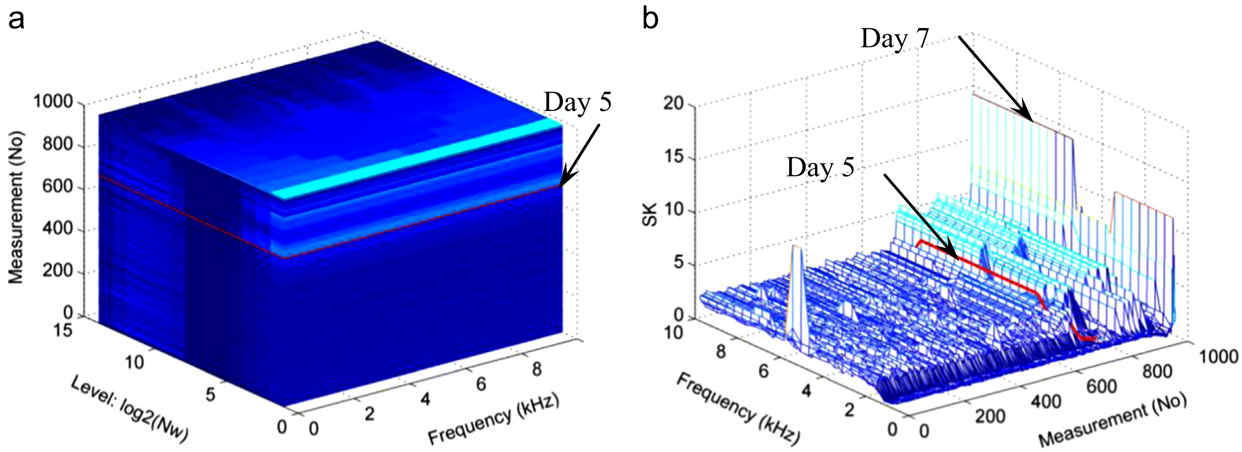

Fig. 11. (a) SK of measurements on a bearing run-to-failure test by using different methods. (a) using kurtogram technique; (b) using ASK.

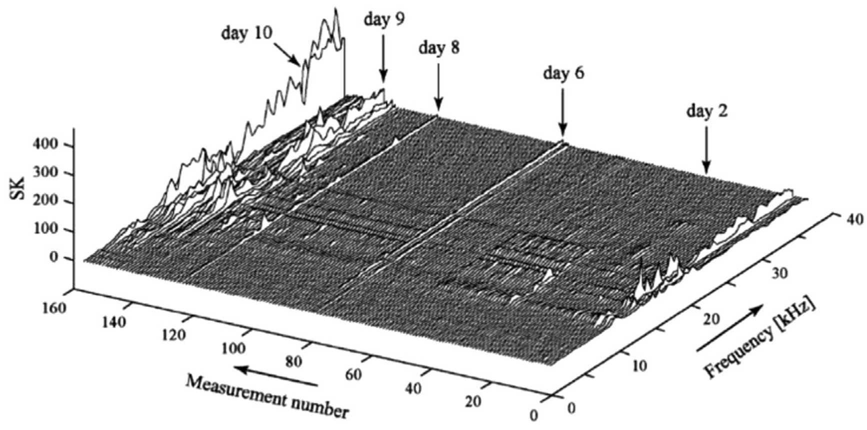

Fig. 12. SK of measurements on a gearbox submitted to an accelerated fatigue test. by using STFT-based SK technique (Fig. 6 in [43])

machinery operating under nonstationary operational conditions, regression parameters were successfully introduced for practical long-term condition monitoring, instead of the traditional features peak-to-peak, RMS, etc. [116]. It can be found that some of the state of the art works mentioned above try to evaluate the prognostics of bearings, because roller bearing defects are progressed in an identical manner without depending on the rolling element type [19].

Since the SK technique has a number of advantages, it would be very useful in the area of prognostics. Nevertheless, these applications have not yet been fully exploited [51]. In order to show the performance of the kurtogram and ASK in the bearing run-to-failure testing, an example is investigated in this section. The experimental data were downloaded at the website of Prognostics Center of Excellence.[2] These data were contributed by Intelligent Maintenance System (IMS), University of Cincinnati. Bearing test rig consisted of four bearings that were of 6000 lb was placed. The rotation speed of the shaft was kept constant at 2000 RPM and a radial load of 6000 lb was placed onto the shaft and bearing by a spring mechanism. All bearings were forced lubricated. The used bearings were Rexnord ZA-115 double row bearings that had 16 rollers in each row, a pitch diameter of 71.5 mm, a roller diameter of 7.9 mm, and a tapered contact angle of 15.17°.The vibration signals were acquired by eight accelerometers from PCB 353B33 that were installed in vertical and horizontal directions. Four thermocouples were also installed in the outer-race of each bearing to record bearing temperature for monitoring lubrication purposes. Vibration signals were collected every 20 min by NI-DAQ Card 6062E data acquisition card. The data sampling rate was 20 kHz and the data length was 20,480 points. More details about the test and the bearing can be found in [117].

The result of bearing run-to-failure data using the kurtosis in the time domain is shown in Fig. 10, while the results using the kurtogram and ASK are shown in Fig. 11(a) and (b), respectively. As can be seen in the figures, a slight increase was found beginning from the fifth day testing. SK technique exhibits high sensitivity to faults in the early stage of development. It is also found that high kurtosis or SK levels often decreases due to 'self-peening' of the bearing flaws. Additionally, STFT-based SK has ever been used for analyzing degradation of gears in run-to-failure tests. Fig. 12 shows SK of measurements on a gearbox submitted to an accelerated fatigue test. Abnormally high values are detected on days 2, 6, 8 and 10. The test was stopped on day 12 due to excessive spall damage [42]. The fluctuation was also found in Fig. 12.

It should be pointed out that degradation analysis for run-to-failure testing using SK (ASK, kurtogram and STFT-based SK) is only empirical in this work, while the systematic application in this field is in process. We only make a few remarks to stimulate this discussion. The overall health indicator of the degradation of run-to-failure test will be a research spot in the future. Moreover, some of the mentioned prognostics techniques require the corresponding information of bearing resonant frequency. Such as, the TLSAE technique [115] applied a narrow band pass filter around a calculated bearing fault frequency before the degradation analysis. SK may be a good technique to determine the narrow band-pass filter. In addition, combined with CI techniques, the energy of the SK may be also considered as a new index for the bearing degradation.

5.2. *Prediction of the remaining useful life*

Remaining useful life (RUL) is mainly conducted on the bearings. RUL of the bearings can be estimated using vibration behaviors and running time of the bearings. Although various algorithms exist for providing RUL, considering the limited number of run-to-failure data sets, the maturation of the prognostic techniques has not been achieved [118]. A general methodology to perform rolling element bearing prognostics using a robust regression curve fitting approach was proposed in [118]. A moving average filter was applied to the time series kurtosis to identify trends over time, and then Bayesian Monte Carlo was used to estimate the RUL of ball bearing [119]. Therefore, recent developments in the dynamic trend analysis were investigated in [120]. Combined with some trend extraction technique, the tendency for the resonance frequencies excited by bearing faults can be developed to reduce as fault size increases.

Vibration monitoring and spectral analysis as a predictive maintenance tool were investigated in [19]. When the overall health indicator of the degradation has been constructed based on SK, prediction of the RUL can be well developed using some trend predicting or CI techniques. Hence, the prediction of RUL via SK may be another hot research spot for predictive maintenance in the future.

6. Concluding remarks

This paper summarizes the research results on the theory of SK and its applications in the fields of fault detection, diagnosis and prognostics of rotating machines, which were published from early 1980 until now. The SK technique extends the concept of the kurtosis, which is a global value, to that of a function of frequency that indicates the impulsiveness of a signal. Its principle is analogous in all respects to the PSD, which decomposes the power of a signal vs frequency using the fourth-order statistics instead of second order. This makes SK be a powerful tool for detecting the presence of transients in a signal. Even though the transient signatures are buried in strong additive noise or interfered with other cyclostationary sources, SK can still automatically indicate in which frequency bands these take place. Thus, SK has recently been broadly utilized in the fault detection, diagnosis of the crucial parts in rotating machines.

It is worth noting that applications of the SK are not merely limited in the fault detection and diagnosis of the rotating machines. It was nowadays also expanded to be used in the fields of termite detection, operational modal analysis (OMA),

[2] http://ti.arc.nasa.gov/tech/dash/pcoe/prognostic-data-repository/

power-quality modeling and analysis, hydromechanics and classification etc. The early subterranean termites were detected by SK in [121]. Combined with discrete wavelet transform, SK was used for the on-site non-destructive measurement of termite activity [122]. Based on the measured responses, the optimized SK was applied to detect harmonic components and to identify the modal parameters of mechanical structures in the fields of OMA [103]. Recently, SK was also applied to detect the tip vortex cavitation noise in a marine propeller [99], and to diagnose electrical machines [123]. Based on the robustness of SK to noise and its capability to detect nonlinearities, a novel application of the SK in power-quality modeling and analysis has been given in [41]. Moreover, to improve the precision of classification and recognition of transient power quality disturbances, an algorithm based on SK and neural network was proposed in [100], in which the maximum value of SK and the frequencies of the signals were chosen as the input of neural network for the classification and recognition. Based on SK and neural network, a classification method for transient power quality was given in [101], where SK values of wavelet transform coefficients were respectively computed based on STFT and WT in this classification method. Another new approach to recognize the transient disturbances using SK was given in [102]. Actually, these mentioned applications are mainly based on great ability of SK in detecting impulsiveness.

The results of this work indicate that the SK is still evolving and has been utilized with some successes in fault diagnosis of the bearings and gears in rotating machines, OMA, diagnostics of the electrical machines etc. It is expected that further research and applications of existing schemes will flourish in the near future, especially in the fields of the prognostics, oriented both to the degradation analysis and prediction of the RUL.

Acknowledgments

The financial sponsorship from the project of National Natural Science Foundation of China (51105085, 51175097, 51475098 and 61463010) and Guangxi Natural Science Foundation (Grant no. 2013GXNSFBA019238) are gratefully acknowledged. The project is also sponsored by SRF for ROCS, SEM and by Guangxi Experiment Center of Information Science (20130312).

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