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Integrating angle-frequency domain synchronous averaging technique with feature extraction for gear fault diagnosis

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A B S T R A C T

Gear fault diagnosis relies heavily on the scrutiny of vibration responses measured. In reality, gear vibration signals are noisy and dominated by meshing frequencies as well as their harmonics, which oftentimes overlay the fault related components. Moreover, many gear transmission systems, e.g., those in wind turbines, constantly operate under non-stationary conditions. To reduce the influences of non-synchronous components and noise, a fault signature enhancement method that is built upon angle-frequency domain synchronous averaging is developed in this paper. Instead of being averaged in the time domain, the signals are processed in the angle-frequency domain to solve the issue of phase shifts between signal segments due to uncertainties caused by clearances, input disturbances, and sampling errors, etc. The enhanced results are then analyzed through feature extraction algorithms to identify the most distinct features for fault classification and identification. Specifically, Kernel Principal Component Analysis (KPCA) targeting at nonlinearity, Multilinear Principal Component Analysis (MPCA) targeting at high dimensionality, and Locally Linear Embedding (LLE) targeting at local similarity among the enhanced data are employed and compared to yield insights. Numerical and experimental investigations are performed, and the results reveal the effectiveness of angle-frequency domain synchronous averaging in enabling feature extraction and classification.

1. Introduction

Condition monitoring and fault diagnosis is an important subject in gear transmission related investigations, where vibration-based techniques have been widely adopted [1,2]. In general, vibration signals measured from a gearbox contain three significant components: periodic meshing frequencies, their harmonics, and random noise. Imperfections due to manufacturing and assemblage tolerances generally result in amplitude and phase modulations. For a healthy gearbox, the meshing frequencies and their harmonics dominate the vibration response. When fault condition is present, additional dynamics are superimposed onto the healthy signal, and different types of faults may have different effects [3]. As such, both the broad-band impulsive components and the random noise become more prevalent.

Typically, a vibration-based technique extracts the fault-related features from vibration signals measured, and uses these features to predict fault occurrence as well as possible type and severity. Methods in both time-domain and frequency-domain have been explored, including statistical analysis, spectral analysis, time-frequency analysis (TFA), and model-based analysis, etc. Time-domain statistical approaches can capture the amplitude and phase modulation if the faults are

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Nomenclature

$\boldsymbol{\alpha}_1, \cdots, \boldsymbol{\alpha}_{N_y}$	eigenvectors
$\boldsymbol{\beta}_k$	extracted feature from the kth gear under health condition
$\boldsymbol{\beta}_i^N$	extracted feature from new data
$\boldsymbol{\beta}_{KPCA}(\mathbf{y})$	extracted feature via Kernel Principal Component Analysis from feature vector $\mathbf{y}$
$\boldsymbol{\beta}_{LLE}(\mathbf{y})$	extracted feature via Locally Linear Embedding (LLE) from feature vector $\mathbf{y}$
$\boldsymbol{\beta}_{MPCA}(\bar{\hat{Y}})$	extracted feature via multilinear PCA from $\bar{\hat{Y}}$
$\lambda_1, \cdots, \lambda_{N_y}$	eigenvalues
ϑ	angular position of the gear
σ	Gaussian kernel parameter
$\varepsilon(\mathbf{W})$	reconstruction error on Locally Linear Embedding
$\varepsilon_1, \varepsilon_2$	distance thresholds in gear fault classification
ϕ	phase of the signal
$\Phi(\mathbf{y}_k)$	nonlinear mapping function in feature space
$\psi_{f_q}(k)$	discrete Fourier Transform of $Y_{f_q}(\vartheta_n)$ at frequency f_q
$\psi(k)$	mean of normalized $\psi_{f_q}(k)$
$\kappa(x_i, x_j)$	Kernel function
$\mathbf{B}(\mathbf{y}_k)$	extracted features via Locally Linear Embedding from baseline feature vector $\mathbf{y}_k$
$\mathbf{B}^{NN(\mathbf{y})}(\mathbf{y}_i)$	extracted features via LLE from the ith closest baseline feature vector $\mathbf{y}_i$ corresponding to $\mathbf{y}$
$\mathbf{C}$	covariance matrix of $\bar{\hat{Y}}_k$
d_i	distances in extracted feature space among the data from baseline gear health conditions
$d_i\prime$	normalized d_i
$d_k^{N(i)}$	Euclidean distance between $\boldsymbol{\beta}_i^N$ and baseline $\boldsymbol{\beta}_k$ corresponding to the k^{th} gear health condition
$\hat{d}_k^N$	normalized $d_k^{N(i)}$
$d^{NN}(\mathbf{y}_k)$	the smallest distance between $\mathbf{y}_k$ and its neighbors
f	frequency
$f_{\text{InputShaft}}$	rotating frequency of input shaft
$\mathbf{K}$	kernel matrix
$\bar{\mathbf{K}}$	Gram matrix
L	number of revolutions kept in the time synchronous average analysis
M	number of signal samples within one gear revolution
N	overall number of gear revolutions
N_a	number of synchronous averaging
N_s	number of angular position sampling points in the spectrogram
N_{seg}	integer number of averaging times
N_y	number of gear health conditions
$Ns(\theta)$	non-synchronous coherent signal
Q	number of frequency points in $\psi_{f_q}(k)$
$R(\theta)$	non-coherent random signal
$S(\theta)$	synchronous coherent signal
$W(n-\vartheta)$	window function for short-time Fourier transform
W_{ki}	reconstruction weights for Locally Linear Embedding
$x(t)$	vibration signal in time domain
$x(\theta)$	vibration signal in angle domain
$X_j(\vartheta, f)$	coefficients from short-time Fourier transform (STFT) of the jth signal segment
$\mathbf{y}_k$	column vector through reshaping the matrix $\hat{Y}_k(\vartheta, \omega)$
$\mathbf{y}_i^{NN(y_k)}$	Euclidean distance between $\mathbf{y}_k$ and its ith neighbor
$Y(\vartheta, f)$	enhanced STFT coefficients via proposed method
$Y_k(\vartheta, f)$	enhanced STFT coefficient corresponding to the kth gear health condition
$\hat{Y}_k(\vartheta, f)$	low-pass filtered $Y_k(\vartheta, f)$
$\bar{\hat{Y}}_k(\vartheta, f)$	centered $\hat{Y}_k(\vartheta, f)$
$Y_{f_q}(\vartheta_n)$	enhanced STFT coefficient at angular position ϑ_n and frequency f_q
$z(\theta)$	complex analytic signal

severe enough to cause significant changes in signals. For example, the crest factor [4], defined as the maximum positive peak value of the signal divided by its root mean square (RMS), is used to detect the presence of local tooth damage. Kurtosis [5], the fourth normalized moment of a signal, can be employed to quantify the number and amplitude of peaks present in