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Method of assessing the state of a rolling bearing based on the relative compensation distance of multiple-domain features and locally linear embedding

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ABSTRACT

To effectively assess different fault locations and different degrees of performance degradation of a rolling bearing with a unified assessment index, a novel state assessment method based on the relative compensation distance of multiple-domain features and locally linear embedding is proposed. First, for a single-sample signal, time-domain and frequency-domain indexes can be calculated for the original vibration signal and each sensitive intrinsic mode function obtained by improved ensemble empirical mode decomposition, and the singular values of the sensitive intrinsic mode function matrix can be extracted by singular value decomposition to construct a high-dimensional hybrid-domain feature vector. Second, a feature matrix can be constructed by arranging each feature vector of multiple samples, the dimensions of each row vector of the feature matrix can be reduced by the locally linear embedding algorithm, and the compensation distance of each fault state of the rolling bearing can be calculated using the support vector machine. Finally, the relative distance between different fault locations and different degrees of performance degradation and the normal-state optimal classification surface can be compensated, and on the basis of the proposed relative compensation distance, the assessment model can be constructed and an assessment curve drawn. Experimental results show that the proposed method can effectively assess different fault locations and different degrees of performance degradation of the rolling bearing under certain conditions.

1. Introduction

The running state of a rolling bearing, as one of the most widely used and vulnerable parts of rotating machinery, directly affects the reliability of the operation of the machinery as a whole. The breaking down of a bearing can result in huge economic losses and even casualties [1,2]. Previous research has mostly concentrated on diagnosing and locating a fault. However, the running state of a rolling bearing changes continuously, gradually declining from initial degradation to complete failure. It is thus important to

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Nomenclature

x_{rms}	root mean square
$x_{p\sim p}$	peak-to-peak amplitude
S_f	shape factor
C_f	crest factor
I_f	impulse factor
CL_f	clearance factor
K_v	kurtosis value
F_C	centroid frequency
F_{MS}	mean-square frequency
F_{RMS}	RMS frequency
F_V	frequency variance
H	the number of spectrum lines
s_i	high-dimensional feature vector
S_{Nj}	high-dimensional feature matrix
r	coefficient correlation
$\boldsymbol{z}_i$	the sample point in high-dimensional space
$\boldsymbol{x}_i$	the sample point in low-dimensional space
y_i	classification label
w	weight matrix
C	the penalty parameter of SVM
b	the bias coefficient of SVM
α_i	Lagrange multiplier
$K(,)$	kernel function
s	kernel parameter
d_R	relative distance
d_C	compensation distance
d_{RCD}	relative compensation distance
d	the reduced dimension number
K	the number of neighboring points
F	classification precision
n	the number of samples, a sample is a segment time sequence of the vibration signal
m	the number of sensitive IMFs
q	the polynomial order

Greek symbols

$\alpha_{i,O,t}$	time-domain feature
$\boldsymbol{\alpha}_{i,O}$	time-domain feature vector comprised of $\alpha_{i,O,t}$
$\beta_{i,O,t}$	frequency-domain feature
$\boldsymbol{\beta}_{i,O}$	frequency-domain feature vector comprised of $\beta_{i,O,t}$
$\alpha_{i,j,t}$	time-frequency feature: time-domain statistical features of the jth IMF
$\boldsymbol{\alpha}_{i,j}$	time-frequency feature vector comprised of $\alpha_{i,j,t}$
$\beta_{i,j,t}$	time-frequency feature: frequency-domain statistical features of the jth IMF
$\boldsymbol{\beta}_{i,j}$	time-frequency feature vector comprised of $\beta_{i,j,t}$
$\gamma_{i,m}$	time-frequency feature: singular value
$\boldsymbol{\gamma}_i$	singular value feature vector of comprised $\gamma_{i,m}$
ξ_i	non-negative slack variables
$\phi(\boldsymbol{x})$	the mapping function in SVM
$\boldsymbol{\omega}$	the normal vector of the hyperplane in SVM

Subscripts

i, j, k, l	positive integers
N_l	N_l is the number of bearing samples whose state is l
t	positive integers (from 1 to 7)
f	positive integers (from 1 to 16)

establish a unified assessment index with which to effectively assess the fault location and the degree of performance degradation. The aim is to realize active maintenance of a rolling bearing through intelligent quantitative assessment, shifting from scheduled or unscheduled maintenance to condition maintenance.

Performance degradation analysis and predictive maintenance methods for mechanical systems have received attention from researchers at home and abroad. A series of intelligent diagnosis and state assessment methods based on the neural network, Weibull distribution, hidden Markov model, and Gauss mixture model (GMM) have been proposed for performance degradation. Empirical mode decomposition (EMD) has been combined with an artificial neural network to realize the fault diagnosis of a bearing [3]. Deep neural networks have been used to mine the rolling bearing fault characteristics [4], and this method also has been used to intelligently classify the fault states. Weibull distribution parameters have been combined with a simplified fuzzy adaptive resonance theory map to predict the residual life of a rolling bearing [5], and this method can be effectively applied to other rotary machinery. The ratio of adjacent singular values has been calculated to construct feature vectors, which have been combined with the hidden Markov model to realize fault diagnosis and performance degradation assessment of a bearing [6]. The matrix $\boldsymbol{S}$ with time-encoded signal processing and recognition as an original feature vector has been calculated, the number of dimensions has been reduced by employing principal component analysis, and the result subsequently combined with the GMM to assess bearing performance degradation [7]. A fuzzy rule has been introduced to a wavelet filter, and the sum of amplitudes of bearing characteristic frequencies and their harmonics has been used as a performance degradation index to realize early fault diagnosis [8]. A second-generation wavelet has been used to extract wavelet packet energy, features extracted employing Fisher discrimination analysis, and the dispersion of the fuzzy c-mean calculated as an index of performance degradation assessment [9].

Among the above methods of assessing the performance degradation of a rolling bearing, there is a need to extract features and to construct a corresponding assessment index. The intelligent assessment of different fault locations and degrees of performance degradation at the same time requires a method of feature extraction, intelligent classification and state assessment.

In recent years, time-domain and frequency-domain statistical features have been widely used in the extraction of vibration signal features for a rolling bearing [10]. Statistical averages in a single time or frequency domain only reflect global information and not local information in the time and frequency domains, and they are not deemed as effective in fault diagnosis and assessment. A series of time-frequency analysis methods, such as the windowed Fourier transform [11], Wigner–Ville distribution [12], and wavelet analysis [13], have thus been proposed. Time-frequency localization has been introduced to the above methods, but problems remain; e.g., it is difficult to determine the window length and to select the basis function. EMD is characterized by