Editorial: Special issue on advanced nonstationary signal processing algorithms and techniques for machinery fault diagnosis and prognosis

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Industrial machinery experiences inevitable state degradation, which affects its performance and structural integrity. Timely diagnosis and prognosis of the degradation are essential to support predictive maintenance decision-making and to guarantee industrial safety and productivity. A major challenge encountered in industrial machinery diagnosis and prognosis is the non-stationarity of condition monitoring signals, primarily due to the complex nature of machinery structures and variations of operating conditions. Industrial machinery can be subject to multisource excitations and fault-induced vibration signals are usually *cyclo*-stationary. At the same time variable operating conditions are prevalent. For instance, wind turbine gearboxes operate under random speed and load conditions due to the randomness of wind speed and direction, while train traction gearboxes operate under variable speed and load conditions when the train passes through high-curvature areas. These variable operating conditions may accelerate the degradation process of machinery and manifest in the condition monitoring data, which impede the diagnosis and prognosis of the machinery. Developing methods to effectively and efficiently process the nonstationary condition monitoring data to achieve accurate and reliable fault diagnosis and prognosis, has therefore drawn much interest over the past decade.

It is foundational to machinery diagnosis and prognosis to understand how faults manifest in the monitored signals. Zhou et al. (2023) review fault-induced vibration signal modulation effects for gears, bearing, and rotors. The effects of variable operating conditions on these fault-induced modulation signatures are detailed. The authors further review time–frequency analysis and signal decomposition methods for diagnosis purposes. Their work contribute to solidifying the foundations of machinery diagnosis and prognosis.

Operating condition information is useful to assist the processing of nonstationary condition monitoring signals. While such information is usually acquired from tachometers or load cells, estimating it from nonstationary vibration signals can potentially not only reduce the cost of hardware but also avoid the difficulty of mounting additional sensors. To this end, Li, Geng, et al. (2023) propose the time–frequency ridge extraction method enhanced with a multi-order probabilistic approach to fully exploit the operating condition information contained within the vibration response, while promising robustness to variations in the running regimes. Li, Zhang, et al. (2023) further develop a time–frequency ridge extraction method that integrates a new cost kernel function and an adaptive search region detection principle for bearing fault diagnosis.

Researchers have made advances to classical signal processing areas including envelope spectrum, mode decomposition, and sparse filtering. For detecting periodic impulses/*cyclo*-stationary components, Chen et al. (2023) propose the product envelope spectrum optimization-gram that fuses the advantages of different generalized envelope spectra. The product envelope spectrum is approximately equivalent to the Fourier transform of the cross-correlation of the periodic components in the corresponding generalized envelopes. Song et al. (2023) propose a smart multichannel mode extraction method based on multivariate variational mode decomposition and manifold learning, which is without predefined parameter tuning and with higher computational efficiency over conventional decomposition methods. Zhang, Xu, and Chen (2023) propose label induced sparse filtering by introducing a fully-connected label layer on top of the conventional sparse representation. The discriminative ability of the sparse learned features was therefore enhanced.

Time-frequency analysis transforms the nonstationary signals into the time–frequency plane, in which both time and frequency information are shown for the extraction of fault-related signatures. Yan et al. (2023) revisit advances in wavelet transforms over the past decade. Particularly, the use of wavelet transforms in conjunction with intelligent algorithms in the sense of improving diagnosis performance and adding interpretability, are newly reviewed. Miaofen et al. (2023) propose an adaptive synchronous demodulation transform by adaptively designing a demodulation term according to the spectral structures of the target signals, and applying it to analyzing time–frequency characteristics of multicomponent signals for machinery fault diagnostics. Ding et al. (2023) propose a slope synchronous chirplet transform and apply it to tacho-less order tracking of rotating machinery. The method is shown to be able to achieve sufficient refined time–frequency representation for the instantaneous frequency close-spaced and trajectory slope mutation signals.

Machine learning algorithms have witnessed rapid and widely recognized progress over the past decade, and many researchers endeavored to use machine learning algorithms for processing and analyzing nonstationary signals, and for exploiting the features hidden in nonstationary signals. Balshaw et al. (2023) highlight the benefits of using latent manifold/indicators from temporal-preserving latent variable models for condition monitoring under variable operating conditions. Five classes of latent space health indicators that capture various manifold perspectives were comprehensively compared and assessed. Xu et al. (2023) propose a global contextual feature aggregation network with favorable diagnostic results under fluctuating variable speed conditions. Jia et al. (2023) propose a deep causal factorization network for domain generalization. The network essentially reveals the invariant casualty between fault representation and label from a causal perspective. Chen et al. (2023) propose Gaussian assumptions-free interpretable linear discriminate analysis to locate informative frequency bands and fault characteristic frequencies for machine condition monitoring. Zhang et al. (2023) develop a novel multi-sensor open-set cross-domain fault diagnosis method that involved a convolutional neural network-based single-sensor feature extraction module, a transformer-based multi-sensor feature fusion module, a weighted adversarial learning scheme, and a threshold-based supervised contrastive loss. Wang et al. (2023) propose a novel scale-independent shrinkage broad learning to detect the abnormal states of wheelset bearings in real-time.

Built upon the rapid development of machine learning algorithms and their satisfactory performance, a new wave of machine learning development is to integrate physical laws such as machine constraints, losses, architecture design guidelines, etc. Ni et al. (2023) propose a physics-informed residual network to tackle the challenges of collecting large amounts of training datasets and compliance with physical law. The network has a physical modal-property-dominant-generated layer, a domain conversion layer, and eventually follows a parallel bi-channel residual learning architecture. Miao et al. (2023) improve the well-known maximum correlated kurtosis deconvolution by configuring the correlated kurtosis as training loss of deep neural networks. Applications on bearing fault diagnosis were presented. Lei et al. (2023) propose a novel prior knowledge-embedded meta-transfer learning approach for few-shot fault diagnosis, with limited training data and scarce test data. As operating speed directly determines the nonstationary pattern of condition monitoring signals, Rao, Zuo, and Tian (2023) explicitly design a speed normalization layer and integrated it into autoencoders to achieve uplifted fault detection performance. The speed normalization branch takes the speed signal as the input and automatically learns a speed normalization function that normalizes the vibration signal to remove the effects of speed variations. Ma et al. (2023) develop a rolling bearing digital twin model based on physical laws and use it to generate training data for transfer learning.

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