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Editorial

Editorial for Special Issue "10th Anniversary of Machines—Feature Papers in Fault Diagnosis and Prognosis"

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Machinery condition monitoring is important in industries. Accurate condition estimation and prediction of the machines can significantly enhance operation safety, increase working efficiency and reduce maintenance costs. Through analysis of the collected machinery condition monitoring data, such as vibration, temperature, images., etc., using signal processing or artificial intelligence methods, the health states of the machines can be well reflected and evaluated. In recent decades, machinery fault diagnosis and prognosis methodologies have been developing rapidly, achieving great success in both academic research and practical engineering problems.

The paper by Almutairi et al. [1] proposes a vibration-based machine learning (VML) approach for diagnosing rotor-related faults in rotating machinery. In addition to rotor faults, anti-friction bearing faults are also included. Vibration-based parameters (both time and frequency domains) are refined to accommodate bearing-related defects.

The paper authored by Afridi et al. [2] is focused on developing a fault prognostic system using long short-term memory for rolling element bearings because they are a critical component in industrial systems and have one of the highest fault frequencies. Compared to other research, feature engineering is minimized by using raw time series sensor data as an input to the model. The model achieves the lowest root mean square error and outperformed similar research models where time domain, frequency domain, or time–frequency domain features are used as an input to the model. Furthermore, using raw vibration data also enables increased generalization of the model.

The paper by Zhang et al. [3] proposes a Euler representation-based structural balance discriminant projection (ESBDP) algorithm for rotating machine fault diagnosis. First, the method maps the high-dimensional fault features into the Euler representation space through the cosine metric to expand the differences between heterogeneous fault samples while reducing the impact on outliers. Then, four objective functions with different structures and class information are constructed in this space. Based on fully mining the geometric structure information of fault data, the local intra-class aggregation and global inter-class separability of the low-dimensional discriminative features are further improved. Finally, they provide an adaptive balance strategy for constructing a unified optimization model of ESBDP, which achieves an elastic balance between global and local features in the projection subspace.

In the paper by Tang et al. [4], a novel training mechanism of multi-scale recursion (MRAE) is designed for the autoencoder in this article, which can be used for accurate feature extraction with a small amount of labeled data. An attention gate-based fusion mechanism is constructed to make use of all useful features in the sense that it can incorporate distinguishing features on different scales. Utilizing large numbers of unlabeled data, the proposed multi-scale recursive semi-supervised deep learning fault diagnosis method with attention gate (MRAE-AG) can efficiently improve the fault diagnosis performance of DNNs trained by a small number of labeled data.

In the paper by Su et al. [5], a fault diagnosis scheme is developed to address the difficulty of feature extraction for planetary gearboxes using refined composite multi-scale fluctuation dispersion entropy (RCMFDE) and supervised manifold mapping. The RCMFDE is first utilized in this scheme to fully mine fault features from planetary gearbox signals under multiple scales. Subsequently, as a supervised manifold mapping method, supervised isometric mapping (S-Iso) is applied to decrease the dimensions of the original features and remove redundant information. Lastly, the marine predator algorithm-based support vector machine (MPA-SVM) classifier is employed to achieve the intelligent fault diagnosis of planetary gearboxes.

In the paper by Maliuk et al. [6], a framework, which aims to improve the bearing-fault diagnosis accuracy using a hybrid feature-selection method based on Wrapper-WPT, is proposed. In comparison with other state-of-the-art methods, the proposed method showed higher classification performance on two different bearing-benchmark vibration datasets with variable operating conditions.

In the paper by Tayyab et al. [7], a performance comparison between all image-processing-based defect diagnosis techniques regarding fault detection accuracy and computational expense is carried out. Moreover, a hybrid ensemble method involving decision-level fusion is proposed, which is far less computationally expensive compared to CNN models, while using them as end-to-end classifiers. The performance of these models is also compared in the case of minimal training data availability and for diagnosis under slightly different operating conditions to ascertain their generalizability and ability to correctly diagnose despite the minimal availability of training data.

Viale et al. [8] study the possibility of implementing a simple classifier in a reduced-dimensionality space of NIs. In addition to a simple decision-tree-like classification method, the process for obtaining NIs can result as a dimension reduction method and, in turn, NIs can be used for other classification algorithms.

The paper authored by Chen et al. [9] propose the processing of a signal according to the continuous wavelet transform and the construction of a three-dimensional matrix containing the time–frequency–space information of the signal. The dimensions of the three-dimensional matrix are reduced by parallel factor analysis, and the time characteristic matrix, frequency characteristic matrix, and spatial characteristic matrix are obtained with tensor decomposition. Through the comparative analysis of the simulation and the experiment, the time characteristic matrix and the frequency characteristic matrix can accurately characterize the normal and fault states of the mechanical equipment. On this basis, the authors established a probabilistic neural network classification model optimized by the improved particle swarm algorithm (IPSO).

Ahmed et al. [10] review the works associated with vibration image representation-based fault detection and diagnosis for rotating machines to chart the progress in this field. They present the first comprehensive survey of this topic by summarizing and categorizing existing vibration image representation techniques based on their characteristics and the processing domain of the vibration signal. They also analyze the application of these techniques in rotating machine fault detection and classification. Finally, they briefly outline future research directions based on the reviewed works.

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