machines

MDPI

Editorial

Deep Learning-Based Machinery Fault Diagnostics

Hongtian Chen [1,*], Kai Zhong [2], Guangtao Ran [1,3] and Chao Cheng [4]

[1] Department of Chemical and Materials Engineering, University of Alberta, Edmonton, AB T6G 1H9, Canada
[2] Institutes of Physical Science and Information Technology, Anhui University, Hefei 230601, China
[3] Department of Control Science and Engineering, Harbin Institute of Technology, Harbin 150001, China
[4] School of Computer Science and Engineering, Changchun University of Technology, Changchun 130012, China
* Correspondence: chtbaylor@163.com

check for updates

Citation: Chen, H.; Zhong, K.; Ran, G.; Cheng, C. Deep Learning-Based Machinery Fault Diagnostics. *Machines* **2022**, *10*, 690. https://doi.org/10.3390/machines10080690

Received: 8 August 2022
Accepted: 8 August 2022
Published: 13 August 2022

In recent years, deep learning has shown its unique potential and advantages in feature extraction and pattern recognition. The application of deep learning to fault diagnosis of complex machinery systems has begun its initial exploration stage. This Special Issue provides an international forum for professionals, academics, and researchers to present the latest developments from theoretical studies and computational algorithm development to applications of advanced deep learning-based machinery system fault diagnosis methods. The contents of these studies are briefly described as follows.

In [1], a possibilistic fuzzy C-means (PFCM) algorithm was proposed to realize the fault classification. Based on the results of fault diagnostics, a fuzzy control strategy was used to solve the fault tolerant control for AUV. Considering the uncertainty of ocean currents, a min-max robust optimization strategy was carried out to optimize the fuzzy controller, which was solved by a cooperative particle swarm optimization (CPSO) algorithm. Simulation and underwater experiments were used to verify the accuracy and feasibility of the proposed method in fault diagnostics and fault-tolerant control.

In [2], the authors proposed a fault detection (FD) model, named as CCA-JITL by using canonical correlation analysis (CCA) and just-in-time learning (JITL) to process scalar signals of high-speed train gears. After data pre-processing and normalization, CCA transformed covariance matrices of high-dimension historical data into low-dimension subspace and maximized correlations between the most important latent dimensions. Then, JITL components formulated the local FD model by utilizing the subsets of testing samples with larger Euclidean distances to training data. A case study demonstrated that a CCA-JITL FD model significantly outperformed traditional CCA models. The proposed approach can also be integrated with other dimension reduction FD models, such as the principal component analysis and partial least squares models.

In [3], the authors designed a Resnet-based classifier with the model-based data augmentation skill, which was applied for bearing fault detection. In particular, a dynamic model was first established to describe the bearing system by adjusting model parameters, such as speed, load, fault size, and the different fault types. Large amounts of data under various operation conditions can then be generated. The training dataset was constructed through the simulated data, which was then applied to train the Resnet classifier. Moreover, in order to reduce the gap between the simulation data and the real data, the envelop signals were used instead of the original signals in the training process. Finally, the effectiveness of the proposed method was demonstrated by the real bearing data. It was remarkable that the application of the proposed method can be further extended to other mechatronic systems with a deterministic dynamic model.

In [4], a local density-based abnormal case removal method was proposed to remove the abnormal cases so as to prevent performance deterioration in industrial operational optimization. More specifically, the reasons why classic case-based reasoning (CBR) would retrieve abnormal cases were analyzed from the perspective of case retrieval. Then, a local density-based abnormal case removal algorithm was designed based on the local outlier factor (LOF) and properly integrated into the traditional case retrieval step. Finally, the effectiveness and the superiority of the local density-based abnormal case removal method was tested on a numerical simulation and the cut-made process of cigarette production. The results showed that the proposed method improved the operational optimization performance of an industrial cut-made process by 23.5% compared with classic CBR and 13.3% compared with case-based fuzzy reasoning.

In [5], in order to improve the performance of fault diagnosis, the authors designed a novel approach by using particle swarm optimization (PSO) with wavelet mutation and least square support vector machine (LSSVM). The implementation process can be concluded as adhering to the following three steps. Firstly, the original signals were decomposed through an orthogonal wavelet packet decomposition. Secondly, the decomposed signals were reconstructed to obtain the fault features. Finally, the extracted features were used as the inputs of the fault diagnosis model. This joint optimization method not only solved the problem that PSO is easy to fall into a local optimum but also improved the classification performance of fault diagnosis effectively. Through experimental verification, the wavelet mutation particle swarm optimization and least square support vector machine (WMPSO-LSSVM) fault diagnosis model has a maximum fault recognition efficiency that was 12% higher than LSSVM and 9% higher than extreme learning machine (ELM). The error of the corresponding regression model under the WMPSO-LSSVM algorithm was 0.365 less than that of the traditional linear regression model.

In [6], traditional fault diagnosis methods were limited in the condition detection of shore bridge lifting gearboxes due to their limited ability to extract signal features and their sensitivity to noises. In order to solve this problem, an adaptive fusion convolutional denoising network (AF-CDN) was proposed in this paper. First, a novel 1D and 2D adaptive fused convolutional neural network structure was built. The fusion of both the 1D and 2D convolutional models can effectively improve the feature extraction capability of the network. Then, a gradient updating method based on the Kalman filter mechanism was designed. Finally, the effectiveness of the developed method was evaluated by using the benchmark datasets and the actual data collected for the shore bridge lift gearbox.

In [7], the authors investigated the event-triggered fault diagnosis (FD) problem. Firstly, an FD fuzzy filter was proposed by using IT2 T-S fuzzy theory to generate a residual signal. The evaluation functions were referenced to determine the occurrence of system faults. Secondly, under the event-triggered mechanism, a fault residual system (FRS) was established with parameter uncertainties, external disturbances and time delays, which can reduce signal transmission and communication pressures. Thirdly, the stability conditions of the faulty residual system were proposed by using the Lyapunov theory. For the energy bounded condition of external noise interference, the performance criterion was established by linear matrix inequalities. The matrix parameters of the target FD filter were obtained via a convex optimization method. Finally, the simulation examples were provided to illustrate the effectiveness and the practicalities of the proposed method.

In [8], the authors thought that the relationship between the indicator reference grades and pre-defined assessment result grades was regarded as a one-to-one correspondence. However, in engineering practice, this strict mapping relationship was difficult to meet. Therefore, a new evidential reasoning (ER) rule-based health assessment model for complex systems with a transformation matrix was adopted. First, on the basis of the rule-based transformation technique, expert knowledge was embedded on the transformation matrix to solve the inconsistent problems between the input and the outputs, which keeps the completeness and consistency of information transformation. Second, a complete health assessment model was established via the calculation and optimization of the model parameters. Finally, the effectiveness of the proposed model was validated in contrast with other methods.

In [9], the authors constructed a spatiotemporal feature fusion network (STNet) to enhance the influence of signal spatiotemporal features on the diagnostic performance during motor fault diagnosis. The network used dual-stream branching to extract the fault features of motor vibration signals via a convolutional neural network and gated recurrent unit (GRU) simultaneously. The features were also enhanced by using the attention mechanism. Then, the temporal and spatial features were fused and input into the SoftMax function for fault discrimination. After that, the fault diagnosis of motor vibration signals was completed. In addition, several sets of experimental evaluations were conducted to verify the effectiveness of the proposed method.

In [10], a data-driven distributed subspace predictive control feeding strategy was proposed. Firstly, the aluminum reduction cell was divided into multiple sub-systems that affect each other according to the position of the feeding port. Based on the subspace method, the prediction model of the whole cell was identified, and the prediction output expression of each sub-system was deduced by decomposition. Secondly, the feeding controller was designed for each aluminum reduction cell subsystem, and the input and output information can be exchanged between each controller through the network. Thirdly, with consideration of the influence of other subsystems, each subsystem solved the Nash-optimal control feeding quantity so that each subsystem realized distributed feeding. Finally, the simulation results showed that the proposed strategy can significantly improve the problem of the uniform distribution of alumina concentration.

In [11], a new belief rule base (BRB) model, called the FFBRB (fuzzy fault tree analysis and belief rule base) was given, which solved the problems existing in the BRB effectively. The FFBRB used the Bayesian network as a bridge, used the FFTA (fuzzy fault tree analysis) mechanism to build the BRB's expert knowledge, used ER (evidential reasoning) as its reasoning tool, and used P-CMA-ES (projection covariance matrix adaptation evolutionary strategies) as its optimization model algorithm. The feasibility and superiority of the proposed method were verified by an example of a flywheel friction torque fault tree.

In [12], the authors introduced a new intelligent fault diagnosis method based on stack pruning sparse denoising autoencoder and convolutional neural network (sPSDAE-CNN). Firstly, a one-dimensional sliding window was introduced for data enhancement. In addition, transforming one-dimensional time-domain data into a two-dimensional gray image can further improve the learning ability of models. At the same time, pruning operation was introduced to improve the training efficiency and accuracy of the network. Actual experiments showed that for the fault of unmanned aerial vehicle (UAV) blade damage, the sPSDAE-CNN model the authors used has better stability and reliable prediction accuracy than traditional convolutional neural networks. The experimental results showed that the sPSDAE-CNN model still has a good diagnostic accuracy rate in high-noise environment. In the case of a signal-to-noise ratio of -4, it still has an accuracy rate of 90%.

In [13], aiming at the characteristics of dynamic correlation, periodic oscillation, and weak disturbance symptom of power transmission system data, an enhanced canonical variate analysis (CVA) method, called SLCVAkNN was presented. In the proposed method, CVA was first used to extract the dynamic features by analyzing the data correlation and established a statistical model with two monitoring statistics. Then, in order to handle the periodic oscillation of power data, the two statistics were reconstructed in phase space, and the k-nearest neighbor (kNN) technique was applied to design the nearest neighbor distance as the enhanced monitoring indices. Further considering the detection difficulty of weak disturbances with the insignificant symptoms, statistical local analysis (SLA) was integrated to construct the primary and improved residual vectors of the CVA dynamic features. The verification results on the real industrial data showed that the SLCVAkNN method can detect the occurrence of power system disturbance more effectively than the traditional data-driven monitoring methods.

In [14], the authors proposed an auxiliary model-based multi-innovation fractional stochastic gradient method. The scalar innovation was extended to the innovation vector for increasing data based on the multi-innovation identification theory. By establishing appropriate auxiliary models, the unknown variables were estimated and the improvement in the performance of parameter estimation was achieved owing to the fractional-order calculus theory. Compared with the conventional multi-innovation stochastic gradient algorithm, the proposed method was validated to obtain better estimation accuracy through the simulation results.

In [15], a process monitoring method based on the dynamic autoregressive latent variable model was proposed in this paper. First, from the perspective of process data, a dynamic autoregressive latent variable model (DALM) with process variables as input and quality variables as output was constructed to adapt to the variable time lag characteristic. In addition, a fusion of Bayesian filtering, smoothing and expectation maximization algorithm was used to identify model parameters. Then, the process monitoring method based on DALM was constructed, in which the process data were filtered online to obtain the latent space distribution of the current state, and two statistics were constructed. Finally, by comparing with the existing methods, the feasibility and effectiveness of the proposed method were tested on the sintering process of ternary cathode materials. Detailed comparisons were given to show the superiority of the proposed method.

As guest editors of this Special Issue, we would like to thank all of the authors for their contributions. We wish that the readers can benefit from the above fifteen papers. We would like to thank *Machines* for giving us the opportunity to serve as the guest editor for the Special Issue. Finally, we would like to thank the reviewers for their excellent job on evaluating these papers.

Funding: This research received no external funding.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Tian, Q.; Wang, T.; Liu, B.; Ran, G. Thruster Fault Diagnostics and Fault Tolerant Control for Autonomous Underwater Vehicle with Ocean Currents. *Machines* **2022**, *10*, 582. [CrossRef]
2. Zheng, H.; Zhu, K.; Cheng, C.; Fu, Z. Fault Detection for High-Speed Trains Using CCA and Just-in-Time Learning. *Machines* **2022**, *10*, 526. [CrossRef]
3. Qian, L.; Pan, Q.; Lv, Y.; Zhao, X. Fault Detection of Bearing by Resnet Classifier with Model-Based Data Augmentation. *Machines* **2022**, *10*, 521. [CrossRef]
4. Peng, X.; Wang, Y.; Guan, L.; Xue, Y. A Local Density-Based Abnormal Case Removal Method for Industrial Operational Optimization under the CBR Framework. *Machines* **2022**, *10*, 471. [CrossRef]
5. Guan, S.; Huang, D.; Guo, S.; Zhao, L.; Chen, H. An Improved Fault Diagnosis Approach Using LSSVM for Complex Industrial Systems. *Machines* **2022**, *10*, 443. [CrossRef]
6. Zhao, R.; Hu, X. An Adaptive Fusion Convolutional Denoising Network and Its Application to the Fault Diagnosis of Shore Bridge Lift Gearbox. *Machines* **2022**, *10*, 424. [CrossRef]
7. Lu, Z.; Zhang, C.; Xu, F.; Wang, Z.; Wang, L. Fault Detection for Interval Type-2 TS Fuzzy Networked Systems via Event-Triggered Control. *Machines* **2022**, *10*, 347. [CrossRef]
8. Li, Z.; Zhou, Z.; Wang, J.; He, W.; Zhou, X. Health Assessment of Complex System Based on Evidential Reasoning Rule with Transformation Matrix. *Machines* **2022**, *10*, 250. [CrossRef]
9. Wang, L.; Zhang, C.; Zhu, J.; Xu, F. Fault Diagnosis of Motor Vibration Signals by Fusion of Spatiotemporal Features. *Machines* **2022**, *10*, 246. [CrossRef]
10. Cui, J.; Wang, P.; Li, X.; Huang, R.; Li, Q.; Cao, B.; Lu, H. Multipoint Feeding Strategy of Aluminum Reduction Cell Based on Distributed Subspace Predictive Control. *Machines* **2022**, *10*, 220. [CrossRef]
11. Cheng, X.; Liu, S.; He, W.; Zhang, P.; Xu, B.; Xie, Y.; Song, J. A Model for Flywheel Fault Diagnosis Based on Fuzzy Fault Tree Analysis and Belief Rule Base. *Machines* **2022**, *10*, 73. [CrossRef]
12. Yang, P.; Wen, C.; Geng, H.; Liu, P. Intelligent Fault Diagnosis Method for Blade Damage of Quad-rotor UAV Based on Stacked Pruning Sparse Denoising Autoencoder and Convolutional Neural Network. *Machines* **2021**, *9*, 360. [CrossRef]
13. Wang, S.; Tian, Y.; Deng, X.; Cao, Q.; Wang, L.; Sun, P. Disturbance Detection of a Power Transmission System Based on the Enhanced Canonical Variate Analysis Method. *Machines* **2021**, *9*, 272. [CrossRef]
14. Xu, C.; Mao, Y. Auxiliary Model-based Multi-innovation Fractional Stochastic Gradient Algorithm for Hammerstein Output-error Systems. *Machines* **2021**, *9*, 247. [CrossRef]
15. Chen, N.; Hu, F.; Chen, J.; Chen, Z.; Gui, W.; Li, X. A Process Monitoring Method Based on Dynamic Autoregressive Latent Variable Model and Its Application in the Sintering Process of Ternary Cathode Materials. *Machines* **2021**, *9*, 229. [CrossRef]