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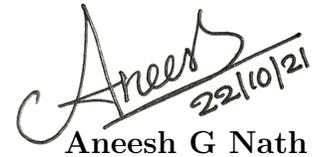
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Dedicated to
My parents,
and
All my teachers.

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List of Symbols

Symbol	Description
V	Set of univariate time-series vibration signals
L	Length of a single-sensor vibration sequence
R_s	Rotational frequency in rpm
S_f	Sensing frequency
S_r	Number of sampling points per rotation
S_o	Number of overlapping points in segmentation
S_l	Segment length
n_s	Number of segments
f_n	Frequency bands
f_{ix}	i^{th} rotational frequency
$amp(f_{ix})$	Amplitude at f_{ix}
A_{amp}	Mean of amplitudes
$\mu(f_{ix})$	Normalized amplitude values
\mathcal{P}	Optimal path matrix
\mathcal{D}	DTW distance matrix
β	Soft-DTW smoothing parameter
F	Forward pass matrix of soft-DTW
B	Backward pass matrix of soft-DTW
ε	Entropy of samples
\mathcal{F}	Base classifier for early classification
θ	class-wise confidence threshold
η	Classifier learning rate
S	Set of state vectors
k	Embedding dimension of phase space
ϵ	Similarity of a state pair
$\theta(\cdot)$	Step function

Symbol	Description
μ	Fuzzy membership function
v	Number of clusters
C	cluster set
m	Fuzziness index
O	Output scores of fusing classifiers
τ	Time delay for embedding
U	Embedding representation of transformer
Q_u	Query matrix
K_u	Key matrix
V_u	Value matrix
$\tilde{\alpha}$	Attention score of sensor fusion
$\hat{\alpha}$	Fault pattern matching score
α	Final attention score
F_{it}	Combined feature vector

Abbreviations

Abbreviation	Description
AB	AdaBoost
AE	Autoencoder
AI	Artificial Intelligence
AM	Attention Mechanism
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
BBN	Bayesian Belief Network
BS	Bent Shaft
BRB	Broken Rotor Bar
CNN	Convolutional Neural Network
CPS	Cyber-Physical Systems
DBA	DTW Barycenter Averaging
DFC	Distinctive Frequency Components
DL	Deep Learning
DT	Decision Tree
DTW	Dynamic Time Warping
EC	Early Classification
EMD	Empirical Mode Decomposition
FCM	Fuzzy C-means Clustering
FD	Frequency-Domain
FDPM	Failure Detection and Predictive Maintenance
FFT	Fast Fourier Transform
FI	Fuzzy Integral
FIC	Fault Information Content
FRP	Fuzzy Recurrence Plot
GA	Genetic Algorithm
GAF	Gramian Angular Field

Abbreviation	Description
GAN	Generative Adversarial Network
GRU	Gated Recurrent Unit
HHT	Hilbert–Huang Transform
HT	Hilbert Transform
ICA	Independent Component Analysis
MA	Misalignment
ML	Machine Learning
k-NN	k-Nearest Neighbor
LDA	Linear Discriminant Analysis
LR	Logistic Regression
LRNN	Local RNN
LS	Looseness
LSTM	Long Short-Term Memory
LVQ	Learning Vector Quantization
MTF	Markov Transition Field
NB	Naïve-Bayes
PCA	Principal Component Analysis
PHM	Prognostics and Health Management
RF	Random Forest
RFD	Rotor Fault Diagnosis
RM	Rotating Machinery
RNN	Recurrent Neural Network
RP	Recurrence Plot
RTB	Rotor Testbed
SC	Shaft Crack
SL	Shallow Learning
SRF	Structural Rotor Faults
STFT	Short-Time Fourier Transform
SVM	Support Vector Machine
TD	Time-Domain
TFD	Time-Frequency-Domain
TS	Time-Series
UB	Unbalance
WT	Wavelet Transform

Preface

The fourth industrial revolution (Industry 4.0) gave rise to a complex industrial production system that has been bolstered by the integration of semantic machine-to-machine communication, cyber-physical systems (CPS), and the Internet of Things. The benefits of early awareness, self-optimization, self-configuration, decision making, and predictive maintenance capability have strengthened Industry 4.0. The rise of a new discipline called prognostics and health management (PHM) was facilitated by advancements in technology, and it has emerged as an essential arm of Industry 4.0. It has been characterized by an important component called failure detection and predictive maintenance (FDPM). It prevents the risk of disastrous failures, major accidents, and unanticipated shutdowns of the whole system, thus safeguarding the fringe benefits such as safety, optimum cost, availability, and reliability. Heterogeneous sensors which are used to collect data from the machine components are incorporated for the virtual modeling of the physical machine working environment. This data caters to the condition monitoring process of FDPM with artificial intelligence (AI) methods to increase the availability and dependability of the system and decrease financial and human losses. A range of mechanical and electro-mechanical systems such as automotive equipment, fans and blowers, aircraft engines, turbines, industrial compressors, conveyor systems, and pumps have rotating machinery (RM) as an integral part of it. Given that, because of the uninterrupted and harsh nature of the operation, they are subjected to both deterioration and failures. Therefore, they require constant monitoring for sustainable

performance. Hence, condition-based monitoring of RM is a core of a maintenance policy formulation, which the research community has extensively investigated nowadays. As a result, AI-based data-driven FDP of RM is on the rise, but unfortunately, the majority of the research in this field focuses only on the faults related to bearing and gear, overlooking the root cause that affects the structural components.

There are diverse methods associated with the RM fault diagnosis; nonetheless, vibration analysis is commonly used as vibration affects the durability and reliability of machines. It became the most appropriate choice for providing fault condition information by means of fault-related spectral component identification. In such a scenario, this thesis focuses on developing AI-based RM fault diagnosis methods for efficiently identifying and solving the root cause of RM issues, protecting the structural integrity of the whole system, analyzing the vibrational characteristics of the faults. To this end, we first categorized the rotor faults based on fault characteristics rather than the conventional component-wise categorization from a ‘cause of vibration’ perspective. The research is directed at making use of the characteristics and the prior knowledge on the fault in automated diagnosis instead of simply adopting data-driven AI approaches. A novel vibration dataset has been developed by a testbed, which simulates the industrial scenarios since various machine learning (ML) or deep learning (DL) techniques mainly used vibration data in the diagnosis process. The testbed dataset often suffers from insufficient and/or imbalanced data of various fault conditions, which eventually leads to a lack of diversity in datasets and overfitting. A time-series (TS) property preserving data augmentation scheme that upkeeps the fault-specific characteristics of data has been proposed to solve this issue. The diagnosis data has been presented in a sequential data representational form to bridge the gap between experimental laboratory data and practical industrial data.

It also handles the unevenly sampled or missing data, different operating speed conditions, and subdues other sensor issues related to raw data, and incorporates

domain-specific fault information. The harmonics of the rotational frequency of RM in the spectrum of vibration is termed as distinctive frequency components (DFC). The symptomatic fault component analysis leads to defining the role of DFC in RM fault diagnosis. Many ML and DL techniques have been used to study the importance of DFC in rotor faults in this research. It is equally important to investigate different input data representation methods such as images, sequences, features, etc. We have analyzed the state-of-the-art TS imaging techniques on vibration data for RM fault diagnosis. The experiments utilized the sequential information provided with the input data, fault-specific component usage, and advanced data modeling paradigms. This work also facilitated the use of an attention mechanism to capture long-term and short-term dependencies of the vibration sequence with transformer architectures. Moreover, advanced learning techniques and methods such as early classification, classifier fusion, transformer networks, etc., have been investigated in this work. The exceptional fault diagnosis results obtained from the proposed techniques and methods mark the importance of this study in RM fault diagnosis.