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An adaptive spatiotemporal feature learning approach for fault diagnosis in complex systems

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ABSTRACT

The machine fault diagnosis is being considered in a larger-scale complex system with numerous measurements from diverse subsystems or components, where the collected data is with disparate characteristics and needs more prevailing methods for data preprocessing, feature extraction and selection. This work presents a novel diagnosis framework that combines the spatiotemporal pattern network (STPN) approach with convolutional neural networks (CNN) to build a hybrid ST-CNN scheme. The proposed framework is tested on two data sets for diagnosing unseen operating conditions and fault severities respectively, to evaluate its generalization ability, which is essential for the application in machine fault diagnosis as not all of the aforementioned scenarios have sufficient labeled data to train a model. The results show that the proposed ST-CNN framework outperforms or is comparable to shallow methods (support vector machine and random forest) and 1D CNN. Through visualizing the activations, it is verified that the spatial features can elevate the diagnosis accuracy, and more general features are determined by the proposed approach to form an adaptive classifier for diverse operating conditions and different fault severities.

1. Introduction

During the evolution of the operation and maintenance strategy of machinery, the condition classification, which tries to distinguish the anomaly from normal and identify the types of anomalies, is an essential task in condition monitoring, diagnosis, prognostics, and health management. With the development of sensing and data availability, the information that can be employed for the condition classification is greatly scaled up in terms of the types of measurements and the volume of data. Numerous examples of this include bearing, gearbox, and rotor system. Besides the widely used vibration (e.g., displacement, velocity, and acceleration), acoustic emission [1–3], sound [4], voltage and current [5–9], and temperature [10,11] are more and more applied in condition classification for diagnosis and prognostics [12,13]. The diverse types of measurements describe the system in different attitudes, while they are probably with different characteristics comparing to the vibration measurements in terms of data processing, feature extraction and selection approaches [14]. Also, the condition classification is being considered in an increasing extent of system, where more measurements are collected from different

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subsystems or components. In this scenario, the condition classification performance is expected to be improved with more information sources, especially when the dependency of the subsystems (the relationship of the fault location to other locations) is taken into account. The fault occurred in wind turbine is a case with this kind of dependency, where the faults attributed to wind wheel (e.g., aero-asymmetry and icing blade) are difficult to be diagnosed by the vibration measurements from the drivetrain (e.g., accelerator on bearing or gearbox). However, when wind speed, rotor speed, and generated power output are provided, the aforementioned faults can be more easily identified [15,16]. In this context, a robust condition classification framework is crucial for the complex systems, which can (i) deal with disparate measurements and different types of data, and (ii) capture the dependency between the components of the system and fuse the features of individual subsystems. Furthermore, as the equipment operates on diverse settings and the combinations of the operating conditions in different subsystems are huge. As a result, it is highly appreciable that the diagnosis algorithm can handle different operating conditions, especially when the model is trained on one operating condition and applied in another.

Intensive research has been conducted on the condition classification of machinery with acceleration widely used. Data preprocessing, feature extraction, and feature selection approaches are proposed for improving the accuracy [17–22]. These feature extraction methods are mostly focused on the vibration (acceleration), and are proven to be extremely useful for the faults that occurred in the bearing, gearbox, etc. However, such kind of feature extraction is based on the domain knowledge of the specific device, namely handcrafted features [23], which may not be applicable in other types of measurements (e.g., acoustic emission, temperature). In this context, an adaptive feature extraction approach is required that can deal with diverse types of measurements.

With the purpose of avoiding manual feature extraction, deep learning approaches have been successfully applied for fault diagnosis, where raw data (usually time-series) is inputted to the deep structures for condition classification [24–28]. Among them, Convolutional Neural Network (CNN) is shown to be highly reliable in dealing with time-series data including univariate [26] and multivariate ones [27,29]. However, the computational cost for this type of model is high because the input data is usually high dimensional, especially when the input is multivariate. As a result, compressed sensing methods are applied to reduce the dimensions of the input [25]. Although the compressed sensing approaches are effective in dimensional reduction, they also sacrifice the temporal features in the original space which may lose the essential features of the faults with pulse impacts (e.g., gear tooth fault in the gearbox).

The traditional feature extraction methods and deep learning structures are mainly focused on the extraction of temporal features (within each individual time-series), the spatial features (that represent the dependency between multiple measurements) are rarely discussed and adopted for the diagnosis. The deep learning structure in the multivariate scenario intends to learn the joint distribution of multiple time-series data. However, the spatial features are still difficult to be learnt as of the characteristics of local receptors (in CNNs) and dimension skewing between the temporal and spatial resolutions of the inputs. As discussed above, the spatial features are important to diagnose the conditions in which the dependency is an indicator of system status, such as wind speed and wind power for a wind turbine.

Motivated by forming a more adaptive feature learning approach that can extract both spatial and temporal features from diverse types of data in an efficient manner, this work presents a spatiotemporal feature learning framework, built on spatiotemporal pattern network (STPN) [30,31], to process multiple time-series data in complex systems and learn spatiotemporal features. The learnt features are then connected to a deep learning structure (CNNs in this work) to implement the condition classification.

The contributions of this work include: (i) proposing an adaptive spatiotemporal feature learning approach for extracting both spatial and temporal features from diverse types of time-series data, (ii) data abstraction process applied in STPN avoids the manual feature extraction and improves the adaptivity of the proposed approach, (iii) the proposed framework comprises STPN and CNNs (ST-CNN) that shows to be more applicable in unseen operating conditions and fault severities, (iv) the presented framework outperforms 1D CNN and shallow methods (Support Vector Machine–SVM and Random Forest–RF) and is computational efficient comparing with 1D CNN, and (v) the interpretation of the learnt features by ST-CNN is explored via Gradient-weighted Class Activation Mapping (Grad-CAM) and the spatial features are shown to be able to elevate the diagnosis accuracy.

The remaining sections are organized as follows. Section 2 provides background and preliminaries including the definition of STPN and CNN basics. The proposed diagnosis framework with STPN and CNN is presented in Section 3. Case studies on two data sets are illustrated in Section 4 as well the discussions and future work. Finally, the paper is summarized and concluded in Section 5.

2. Background and preliminaries

2.1. Spatiotemporal Pattern Network (STPN)

Symbolic dynamics filtering (SDF) is formed with the assumption that a symbol sequence (generated by the time-series) can be modeled as a Markov chain of order D (namely the depth of the Markov machine in the presented method) which captures the characteristics of the time-series [32,33]. Data abstraction is first implemented in SDF, to generate the symbol sequences of the time-series (sub-systems) including data preprocessing and discretization. The discretization transforms the time-series into a symbol sequence (namely partitioning in the symbolic dynamics literature). For a system consisting