Fault Diagnosis in Industries: How to Improve the Health Assessment of Rotating Machinery

Francesca Calabrese(✉), Alberto Regattieri, Marco Bortolini, and Francesco Gabriele Galizia

Department of Industrial Engineering (DIN), University of Bologna, 40136 Bologna, Italy
{francesca.calabrese9,alberto.regattieri,marco.bortolini3,
francesco.galizia3}@unibo.it

Abstract. Rotating machinery like pumps, compressors, and engines, are widespread in industries. A failure in one or more of their components, e.g., rolling bearings and gearboxes, may cause system breakdowns or even catastrophic events. Hence, fault diagnosis of rotating machinery is achieving great attention from both the industrial and academic fields. After collecting signals from sensors mounted on different locations, different condition monitoring techniques, e.g., vibration analysis and acoustic emissions, are usually applied to get accurate information on machinery health conditions. The most challenging step in the fault diagnosis process is feature extraction from collected signals, which describe the fault behavior synthetically while retaining as much information as possible. In intelligent fault diagnosis, the extracted features feed Machine Learning algorithms for fault classification. However, given the high number of variables that result from feature extraction, dimensionality reduction should be performed to improve the classification accuracy and training times of intelligent methods. In the literature, the problem of dimensionality reduction is faced through feature selection and feature fusion. These methods are often combined in different ways, resulting in a broad range of possible solutions. In this paper, a bibliometric analysis is conducted to discover trends over time and identify the connections between the different activities of the fault diagnosis process using dimensionality reduction techniques. The present study's main result lies in identifying the most promising frameworks for industrial applications of fault diagnosis using dimensionality reduction.

Keywords: Fault diagnosis · Rotating machinery · Dimensionality reduction · Feature selection · Feature fusion

1 Introduction

Rotating machinery is very common in industries, and its failure may cause system breakdowns or even catastrophic accidents [1]. Fault diagnosis aims to monitor the health condition of components and detect the occurrence of a failure. Among fault diagnosis techniques, such as vibration-based, current-based, and acoustic emission-based, the vibration-based diagnostic is the most adopted, as vibration signals can describe the

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dynamic behavior of rotating machinery [2]. Given the increasing complexity of systems, physics-based models often fail to describe the system behavior, especially under varying operating conditions. Therefore, data-driven methods based on Machine Learning (ML) are increasingly adopted for vibration-based fault diagnosis of rotating machinery.

The process of fault diagnosis of rotating machinery using a data-driven approach consists of two main steps. First, it is necessary to process and transform raw signals to extract useful fault information [3]. Then, faults are identified using classification models using the extracted information. The most challenging step is the first one, which basically includes signal processing techniques and feature extraction methods. Signal processing consists of processing raw signals in the time, frequency, or time-frequency domain to extract features [4]. Features can be defined as parameters derived from the measured signals that robustly indicate the presence of rotating machinery faults [5]. These features should have two main properties. First, they should be relevant to reveal the health condition of the system; second, they should be non-redundant to reduce the computational complexity and training times of ML algorithms used for fault diagnostic. However, both signal processing and feature extraction increase the number of variables, i.e., the features of the dataset. Therefore, it is necessary to identify a smaller feature set that best represents the system's health condition [6].

In the context of data science, the task of reducing the number of variables in a dataset is referred to as Dimensionality Reduction (DR) [7]. It can be performed by feature selection or feature fusion methods. In the first case, the dimension of the dataset is reduced by selecting the subset of features that most contribute to the classification accuracy and eliminating those that contain redundant information. In the second case, original features are subject to different kinds of transformation to produce features with more informative content [8].

In the context of fault diagnosis, the distinction among different dimensionality reduction methods is not always clear. In particular, feature extraction is often used for signal processing, feature learning, and feature fusion.

This paper aims to provide a systematic classification of the existing literature on dimensionality reduction methods adopted in fault diagnosis of rotating machinery. To this purpose, a bibliometric analysis is first conducted to identify the publishing trend and relevant topics. Then, a co-occurrence analysis is conducted on the author keywords in order to identify the activities conducted for dimensionality reduction and their connections. Finally, a systematic classification of existing frameworks is proposed. The Scopus database is used to collect the documents and perform trend and citation analyses, while the freely available software VOS viewer is used to construct the bibliometric map and perform the co-occurrence analysis [9].

The remainder of this paper is organized as follows. Section 2 is dedicated to the description of the state-of-the-art (publishing trend and identification of most relevant papers) on dimensionality reduction for intelligent fault diagnosis of rotating machinery. In addition, the connections between activities conducted for dimensionality reduction that emerged from the co-occurrence analysis are described. Section 3 is dedicated to the description of the identified frameworks and the classification of existing papers into the identified frameworks. Finally, the main results and conclusions are presented in Sect. 4.

2 Bibliometric Analysis

This section describes the bibliometric analysis of papers related to dimensionality reduction techniques for fault diagnosis of rotating machinery. The papers are collected from the Scopus database through the following search query:

$$\left(\begin{array}{c} diagnos^{*}\,OR\,faultidentification\,OR\,faultdetection \\ OR\,prognos^{*}\,healthmanagement \\ AND \\ feature^{*}\,extraction\,OR\,feature^{*}\,selection\,OR\,feature^{*}\,learning\,OR \\ feature^{*}\,fusion\,OR\,feature^{*}\,construction\,OR\,feature^{*}\,engineering\,OR \\ dimension^{*}\,reduction \\ AND \\ rotat^{*}\,machin^{*} \end{array}\right) \tag{1}$$

In total, after the elimination of non-English papers, 1639 documents were found. The publishing trend over time is shown in Fig. 1. Unlike results obtained in [10], in which a bibliometric analysis on fault diagnosis of rotating machinery was conducted, the number of published papers starts to increase after 2003, showing a delay of 6 six years regarding the more general topic of fault diagnosis. Since then, an increasing number of papers have been published. In particular, 2017 and 2019 are the year with the maximum increase with respect to the previous year.

Among the 1639 documents, only 5 reviews are present. However, they have mainly focused on signal processing techniques rather than dimensionality reduction techniques. In particular, time-frequency domain analysis methods and AI methods [2], entropy theories [1], and cyclostationary analysis [11] are reviewed for early fault diagnosis of rotating machinery.

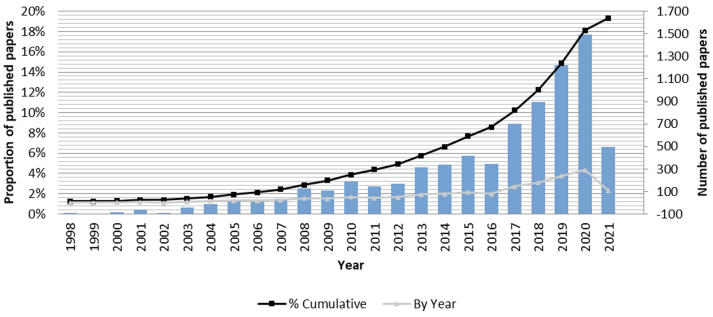

Fig. 1. Publishing trend

Citation analysis has been conducted to analyze the most influential papers in this context. Table 1 shows the 10 most cited papers with the corresponding Journal.

In all these works, the importance of dimensionality reduction for fault diagnosis is highlighted. With time, the focus moved from the use of signal processing and feature extraction methods towards feature selection after feature extraction first and the

Table 1. The top 10 cited articles.

No	Article	Journal	Number of citations
1	Jia et al. (2016) [12]	Mechanical Systems and Signal Processing	841
2	Samanta et al. (2003) [13]	Mechanical Systems and Signal Processing	553
3	Lu et al. (2017) [14]	Signal Processing	366
4	Bin et al. (2012) [5]	Mechanical Systems and Signal Processing	351
5	Chen et al. (2017) [15]	IEEE Transactions on Instrumentation and Measurement	323
6	Hu et al. (2007) [16]	Mechanical Systems and Signal Processing	319
7	Sugumaran et al. (2007) [17]	Mechanical Systems and Signal Processing	308
8	Lei et al. (2007) [18]	Mechanical Systems and Signal Processing	301
9	Lei et al. (2008) [19]	Expert Systems with Applications	289
10	Shao et al. (2017) [20]	Mechanical Systems and Signal Processing	257

use of unsupervised feature learning then. The first two papers in Table 1 represent a very breakthrough in the literature, applying for the first time in the context of fault diagnosis feature extraction and deep learning. In 2003, an intelligent fault diagnosis method for rolling bearings based on signal processing techniques and time-domain feature extraction had been proposed to improve training time and accuracy of ANNs for fault classification [13]. In 2007, feature selection methods were applied after feature extraction [16–19]. In 2012, Bin et al. proposed a novel energy feature that allows selecting the most appropriate processed signal for further feature extraction [5]. Finally, in 2016 and 2017, deep neural networks are proposed with the primary goal of avoiding the time-consuming and labor-intensive activity of manual feature extraction [12, 14, 15, 20]. Indeed, in contrast to shallow structures, deep structures can automatically learn discriminative features in an automatic and unsupervised manner.

In these works, five main activities can be distinguished: signal processing, feature extraction, feature selection, feature fusion, and feature learning. A co-occurrence analysis on the paper keywords is conducted to identify groups of activity, tools, and methods usually performed. In Fig. 2, the resulting graph obtained with the software VOSviewer is shown, where the size of circles is proportional to the number of occurrences of a keyword.

Because only keywords with a minimum number of occurrences equal to 6 are visualized in the graph, 126 keywords are shown in the graph. In addition, the keywords fault diagnosis and rotating machinery are not visualized because they are linked to all other

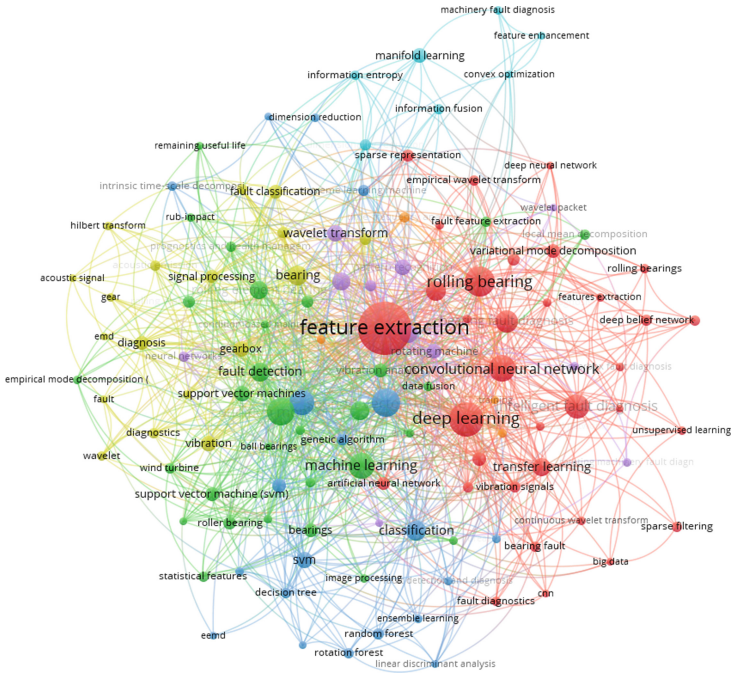

Fig. 2. Keyword-based co-occurrence analysis

keywords. From Fig. 2, it can be seen that the most occurred keyword is feature extraction, which demonstrates the importance of this task in the intelligent fault diagnosis process. In particular, feature extraction has been used in 218 papers and has often been used together with feature selection, signal processing, dimensionality reduction, and information fusion. Feature selection occurred 54 times and is connected with feature extraction, signal processing, and dimensionality reduction. Signal processing has been used in 16 papers and is linked with feature extraction and feature selection. Dimensionality reduction occurred 20 times and is connected with feature extraction, feature selection, and information fusion. Finally, a separated group is represented by feature learning, which occurred only 11 times and is not connected with any of the other tasks.

To better understand how dimensionality reduction is usually performed, only papers using the keywords corresponding to the tasks identified in the most cited papers are analyzed. In addition, because of the high number of papers that face these topics, only the last three years (from 2019 to 2021) are considered to identify existing frameworks.

A deep investigation of the collected papers allowed to draw the following considerations. First, the reduction of the number of variables is classified as a dimensionality reduction technique in few cases only. Therefore, if papers are searched by using only the keyword dimensionality reduction in the search query, many documents implementing such a task do not appear. In addition, dimensionality reduction is also associated with traditional feature extraction and signal processing, which are often used indistinctly to extract statistical features in the time, frequency, and time-frequency domains. However,

in this sense, they cannot be considered dimensionality reduction techniques. Second, the number of papers using the keyword feature learning is minimal. This is because feature extraction or deep learning refers to the automatic and unsupervised learning of high-level features. However, feature extraction and feature learning are very different from each other. In the first case, the statistical features to extract are set by the user. In the second case, at each layer of the deep architecture, a certain transformation is realized. However, no human intervention is required. In addition, deep learning is a tool; thus it is also used for other purposes, e.g., diagnostics and prognostics. This results in the impossibility of identifying when they are actually used for feature learning or diagnostics and prognostics. Finally, the use of feature fusion is limited. Very often, information fusion and sensor data fusion are used instead of feature fusion. However, they refer to the fusion of multiple signals collected through different sensors and not the combination of previously extracted features. In addition, feature extraction is also used when multiple features are combined to provide more accurate and robust features.

The variability in the terminology causes great confusion when approaching the dimensionality reduction problem for fault diagnosis. For this reason, a systematic classification of existing frameworks and approaches for dimensionality reduction is needed.

3 Systematic Classification of Existing Approaches

The proposed classification of the connections held between the activities conducted for dimensionality reduction is shown in Fig. 3. Basically, dimensionality reduction for fault diagnosis of rotating machinery is realized through two activities: feature selection and feature fusion, which are almost always applied after signal processing, feature extraction, or feature learning. Signal processing includes all those activities for noise removal or signal transformation into frequency and time-frequency domains. After signal processing, feature extraction or feature learning can be performed. In the first case, statistical features are extracted from raw or processed signals. It cannot be considered a dimensionality reduction technique as it reduces the number of samples while increasing the number of variables of the dataset. In the second case, features are automatically learned from raw or processed data. Thus, feature learning is an alternative way to automatically learn the optimal data representation from raw or processed signals [21, 22]. If the number of features manually extracted or/and automatically learned is too high, feature selection or feature fusion are conducted before fault classification, which effectively corresponds to two distinct ways to perform dimensionality reduction.

In Table 2, examples of papers implementing the identified approaches are summarized. In [23], signals are first transformed into the frequency domain by means of a signal processing technique before the extraction of statistical features. Then, the most sensitive features are selected through the Relief algorithm. A similar approach using different techniques for signal processing, feature extraction, and feature selection can be found in [24–26]. In [27], only feature extraction and selection are performed. Hence, statistical features are extracted directly from raw signals without a previous signal processing technique; then, a Genetic Algorithm is used for feature selection.

Similarly, in [28], features are first extracted from raw signals. Then, feature selection is performed in three steps: a classification model, a correlation analysis, and the

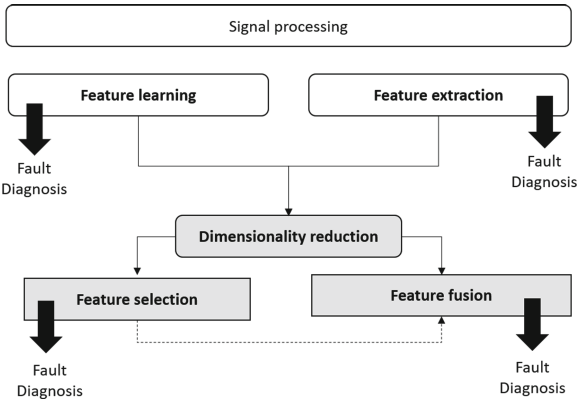

Fig. 3. Classification of activities and approaches

Principal Component Analysis (PCA). PCA is usually considered a feature extraction method. However, in this work, the obtained Principal Components are weighted and fused to obtain the score ranking of the original features. Hence, since the resulting feature set is made of original features, it is more appropriate to consider the PCA adopted in this work as a feature selection method. In [29], the PCA method has been used as a feature fusion method after signal processing and feature extraction. In [30], a Genetic Programming (GP) made of 7 layers is applied for signal processing, feature extraction, feature construction, and feature combination. The last two layers correspond to a two-step feature fusion. In [31], both feature extraction and feature learning are applied in parallel before feature selection. In particular, two signal processing techniques are applied before feature extraction. The first technique generates signals that are used to learn the features through a deep neural network. The other technique is applied to extract a second set of features, consisting of statistical features extracted from processed signals in the time and frequency domains. Finally, the distance-based feature selection method is applied to both feature sets to select the sensitive features that will be used for fault diagnosis. Hence, four different frameworks are identified, which include: signal processing, feature extraction, and feature selection; feature extraction and feature selection; signal processing, feature extraction, and feature fusion; signal processing, feature extraction and feature learning (in parallel), and feature selection.

Table 2. Adopted approaches.

Ref.	Signal processing	Feature extraction	Feature learning	Feature selection	Feature fusion
[23–26]	X	X		X	
[27, 28]		X		X	
[29, 30]	X	X			X
[31]	X	X	X	X	

4 Conclusions

In this paper, the problem of dimensionality reduction for fault diagnosis of rotating machinery is investigated. In particular, a bibliometric analysis is conducted to discover publishing trends and typical activities involved in the fault diagnosis process. Results show that, from 2003, an increasing number of papers related to this topic have been published. In particular, a breakthrough is represented by deep learning models, which have been investigated since 2016 for automatic feature learning. These models allow avoiding the time-consuming and knowledge-based feature extraction. However, deep learning has numerous drawbacks from the industrial point of view, including the need for a large amount of high-quality data that is difficult to collect for industries [10]. Therefore, many studies are conducted on traditional dimensionality reduction techniques, like feature selection and feature fusion, which allow identifying relevant features for training the models that provide the best fault classification accuracy. Given the low computational time required by these methods, the so-identified features can be extracted in streaming for future inference, enabling the real-time fault diagnosis of rotating machinery [32]. A co-occurrence analysis based on author keywords has also been conducted in this study to identify typical frameworks for intelligent fault diagnosis of rotating machinery using dimensionality reduction techniques. It resulted that only feature selection and feature fusion can be considered dimensionality reduction techniques and that they can be included in four different frameworks. After signal collection, signals may be processed in one of the analysis domains; then, statistical features can be extracted from raw signals and processed signals; finally, relevant features can be selected or constructed by feature selection or feature fusion techniques, respectively. Features can also be selected or fused using features obtained from feature extraction and feature learning.

A systematic classification of existing literature on dimensionality reduction into four different frameworks has been conducted in this study. However, typical models for the realization of this task are not reviewed. Therefore, a comprehensive literature review of such methods will be the object of future studies.

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