Enhancing Data-driven Vibration-based Machinery Fault Diagnosis Generalization Under Varied Conditions by Removing Domain-Specific Information Utilizing Sparse Representation

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Abstract

This paper introduces a novel approach to machinery fault diagnosis, addressing the challenge of domain generalization in diverse industrial environments. Traditional methods often struggle with domain shift and the scarcity of balanced, labeled datasets, limiting their effectiveness across varied operational conditions. The proposed method leverages the abundance of healthy machinery signals as a reference for extracting domain-specific information. By doing so, it removes the domain-related variances from the observation signals, focusing on the intrinsic characteristics of faults. The methodology is validated with a case study, demonstrating enhanced diagnosis accuracy and generalization capabilities in unseen domains. This research contributes to the field of vibration-based intelligent fault diagnosis by providing a robust solution to a long-standing problem in machine condition monitoring.

1. Introduction

In the domain of industrial maintenance, ensuring the reliability and efficiency of rotating machinery is a central challenge. Among the various strategies employed, vibration-based fault diagnosis stands out as a proven technique for preemptive detection and mitigation of potential failures (Randall, 2010).

The advent of the Industrial Internet of Things (IIoT) and the proliferation of sensor technologies have led to an unprecedented availability of machinery data. This, in turn, has facilitated the application of intelligent diagnosis methods (Liu, Yang, Zio, & Chen, 2018) which showed impressive performance. Despite this, the use of these methods in real industrial scenarios has been proven difficult, mainly because it relies on a central assumption which is often hard to meet. Indeed, most Machine Learning (ML), including Deep Learning (DL) diagnosis techniques learn a representation of the training data in order to generalize to unseen examples. The unseen examples, also referred to as test data, must then follow the same distribution as the training data to ensure effective generalization by the model. The unpredictability of industrial environments and the varying working conditions of rotating machines significantly challenge this assumption. This results in overfitting on the working conditions the model has been trained on, and leads to a dramatic decrease in performance when conditions change.

Transfer learning has emerged as a popular strategy to address this challenge, aiming to leverage knowledge from one domain to improve performance in another. Specifically, methods employing distance metrics to bridge the gap between source and target domains have shown promise. However, these approaches typically assume availability of the target domain data during training, a scenario often impractical in the field. (Azari, Flammini, Santini, & Caporuscio, 2023). Indeed, despite the wide availability of surveillance data provided by IIoT sensors, the vast majority of available data predominantly reflects healthy working conditions, as faults are infrequent.

Domain generalization is then a more fitting problem formulation for situations where the target domain remains unknown during the model training phase. Unlike domain adaptation, domain generalization aims to produce models which generalize well to domains unseen during training. For instance, in (Zhao & Shen, 2023) the authors proposed a mutual-assistance network for semi-supervised domain generalization, while in (Shi et al., 2023) a dynamic weighting strategy and a batch spectral penalization regularization term was employed to tackle the domain generalization problem. In (Jia, Li, Wang, Sun, & Deng, 2023) a deep causal factorization network is used, taking advantage of the causal properties in bearing signal models. The authors of (Zheng et al., 2021) combined apriori expert knowledge on vibration analysis and a deep neural network to generalize to unseen operating conditions. In (Wang et al., 2023) the authors used domain-specific discriminators to explicitly remove domain-specific information from the signals, creating domain-invariant representation, yielding to better generalization to unseen working conditions. However, the current landscape of domain generalization solutions is primarily characterized by complex deep learning architectures. Although effective, these architectures tend to obscure the interpretative transparency of these models, thus contributing to the 'black box' phenomenon often cited as a major pitfall of state-of-the-art models. Consequently, recent works such as (Kim et al., 2024) proposed an explainable diagnosis technique for single-domain generalization tasks using a priori knowledge to produce domain-invariant representations, showing increased performance on unseen target domains.

By tackling the domain shift challenge, our research introduces a novel preprocessing technique tailored to address the domain shift problem and the challenges induced by non-stationary vibration signals. This technique leverages the abundance of healthy signal data as a reference for identifying domain-specific information. We operate under the assumption that healthy signals contain such domain-specific information, which can impede the generalization capabilities of the models.

This approach aims to systematically eliminate domain-specific characteristics from the diagnosis data using advanced signal processing techniques, thereby isolating the intrinsic characteristics of faults. By focusing on the features that are truly indicative of machinery health, irrespective of operational conditions, our method proposes a step towards achieving domain-agnostic fault diagnosis. This approach allows us to benefit from the excellent performance state-of-the art intelligent models without increasing their complexity to achieve cross-domain fault diagnosis tasks.

The contributions of this paper are as follows:

1. A sparse representation-based signal processing technique is proposed to decompose the non-stationary noisy signals into their relevant components
2. Decomposed reference healthy signals are used to remove domain-specific information from the observation signals
3. The domain-invariant signals from a source domain are used train a simple classification model. Preprocessed signals from target domains are used to validate the generalization improvements on domains unseen during training.

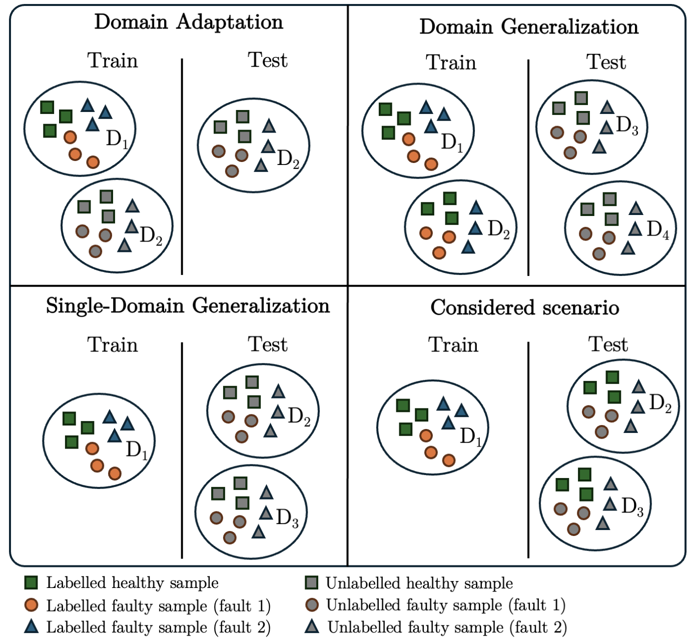

Figure 1. Generalization paradigms

The rest of this paper is organized as follows: in section 2 the method for domain-specific information removal is exposed, in section 3 an experimental setup and protocol is proposed to validate said method, and in section 4 the results are presented.

2. Background

2.1. Domain generalization

Let us consider a rotating machine having N different working conditions, which translate into N different domains noted as $D^i = \{(x_j^i, y_j^i)\}_{j=1}^{n_i}$, where (x_i, y_i) is the data-label pair for the jth sample in the ith domain. Let us also consider the situation where the label space is shared across domains, but only one domain is fully labelled and accessible during training, while in all others only healthy samples are known as such and are unseen until testing. This constitutes a realistic data availability scenario, where healthy data is abundant but fault data is scarce and usually represent a small subset of possible working conditions. The differences between domain adaptation, domain generalization, single-domain generalization and the Considered scenario are illustrated in Figure 1.

In this single-domain generalization scenario, the goal is to train a classifier considering the limited data availability and then demonstrate the generalization capability on unseen domains.

2.2. Vibration signals under time-varying working conditions

Rotating machines operating under varying working conditions not only cause the domain shift problem. Their vibration signals also contain specific challenges which makes them hard to process.

Vibration signals generated by rotating machines operating under constant or almost-constant working conditions can be described using Eq. 1.

$$x(t) = d(t) + r(t) + n(t), \qquad (1)$$

where $d(t)$, $r(t)$ and $n(t)$ refer to deterministic, random and background noise contributions respectively. Under constant operating conditions, we can formulate several assumptions on the nature of these contributions. Deterministic contributions are almost-periodic as they are phase-locked to the shaft angle, and the random part is often described as cyclostationary (Antoni, Bonnardot, Raad, & El Badaoui, 2004), while background noise is often assumed to be Gaussian white noise coming from sensor and environmental noise.

Under varying operating conditions however, significant changes occur in the vibration signals of rotating machines which significantly challenge the assumptions previously made. For instance, when the rotating speed of the machine varies in time, the deterministic contributions are no longer periodic, while cyclostationary contributions become cyclo-non-stationary (Abboud et al., 2016). This emphasizes the enhancements outlined in this study, which will be discussed in the following section.

3. Proposed method

A preprocessing technique aiming to reduce the effects of domain shift induced by varying working conditions is proposed. The preprocessing technique is composed of two main tasks: the vibration signals must first be decomposed into their relevant parts, then the decompositions from reference signals are used to identify and remove domain-specific information from the signals in each domain. An overview schema of the method is illustrated in Figure 2.

3.1. Decomposition of vibration signals based on Sparse Representation

Many signal processing techniques have been proposed over the years to accurately handle vibration signals produced by rotating machines operating under time-varying working conditions. Considering the shortcomings of classical frequency-domain techniques, methods such as time-frequency analysis are often a suitable tool to handle these signals (Zhang & Feng, 2022). However each time-frequency has its own drawbacks, and choosing the right technique is often difficult. In this study, the Sparse Representation (SR) (Feng, Zhou, Zuo, Chu, & Chen, 2017) framework is adopted to decompose the vibration signals using a redundant basis.

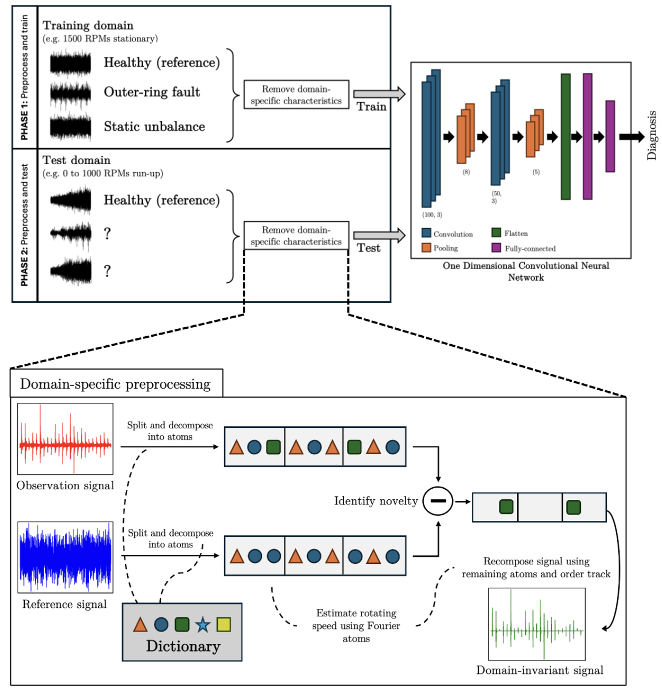

Figure 2. The proposed method to produce domain-irrelevant signals

Considering the morphological specificities of the different contributions present in vibration signals, SR allows not to be limited by the choice of a single basis, which might not be able to accurately represent all types of contributions. Instead a union of basis can be used, with the assumption that a more efficient and sparse representation can be achieved.

This union of basis is referred to as a dictionary, and each element of the dictionary is an atom. Several dictionaries have been proposed over the years, for instance the author of (Qin, 2018) used an impulse wavelet along with Fourier atoms to denoise bearing fault signals, while in (Cai, Selesnick, Wang, Dai, & Zhu, 2018) the authors used a union of a Discrete Cosine and a Short-time Fourier basis to diagnose faults in a gearbox.

These analytic dictionaries are very useful to identify components whose morphological characteristics, such as the natural frequency of the system, are known a priori. However in most cases there's a very limited amount of prior information available on industrial machines. Therefore, this study adopts a minimalistic dictionary approach, accommodating both deterministic and stochastic elements in vibration signals. This is achieved through integrating Fourier and Unit bases, representing these contributions respectively.

SR can be achieved through either greedy methods like Matching Pursuit (MP) (Mallat & Zhang, 1993), or optimization-based techniques such as basis pursuit (BP) (Chen, Donoho, & Saunders, 1998). In the latter, the optimization objective is to minimize the reconstruction error, regularized by the norm of the sparse vector, expressed in Eq. 2.

$$\min_{x} \left\{ F(x) = \frac{1}{2}\|y - Ax\|_2^2 + \lambda\psi(x) \right\}, \tag{2}$$

where $y \in R^{N\times 1}$ is the input signal of size N, $A \in R^{N\times K}$ is the dictionary where $K > N$, x is the sparse vector, λ is the regularization parameter and ψ is a sparsity-inducing penalty.

In this study, the Generalized Minimax Concave (GMC) penalty is used due to its ability to overcome the amplitude underestimation issue associated with the l_1 penalty, while still preserving the convexity of the overall optimization objective, as highlighted by (Selesnick, 2017). The GMC penalty, defined in Eq. 3, serves as a key component in our approach.

$$\psi_{\text{GMC}}(x) = \|x\|_1 - \min_{v} \left\{ \|v\|_1 + \frac{\gamma}{2\lambda}\|A(x - v)\|_2^2 \right\}, \tag{3}$$

where $\gamma > 0$ controls the convexity of the GMC penalty, which is set at $\gamma = 0.8$ as advised in (Selesnick, 2017). The λ term is the regularization parameter. In this study, we set empirically $\lambda = 1.4$.

There are many algorithms designed to find the minimizer to this convex optimization problem. In this work we use the forward-backward splitting algorithm.

An example of decomposition using the proposed method is illustrated in Figure 3 where a signal containing a rolling element bearing fault is decomposed using Eq. 2. The different contributions from the Fourier and Unit basis are represented in blue and red respectively.

3.2. Removal of domain-specific components from the observation signals

After windowing and decomposing the signal using the proposed SR method, decompositions of healthy signals from each available domain are utilized as reference. It is assumed that these signals contain domain-specific characteristics that do not carry relevant diagnosis information and may contribute to the domain-shift issue. In every domain, atoms

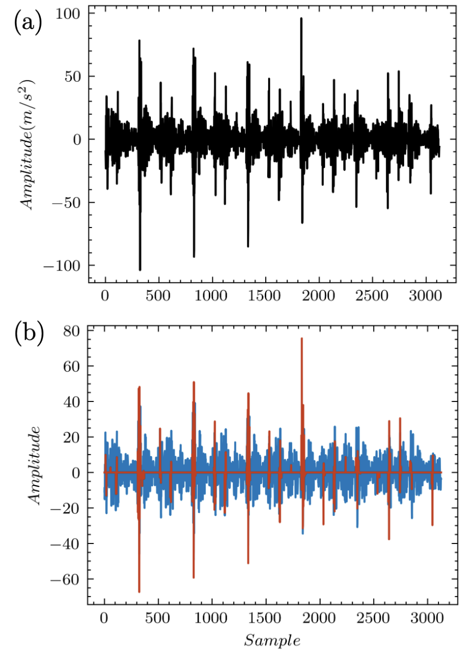

Figure 3. Decomposition of a signal containing an Inner Ring fault (a), into its deterministic contribution (blue in (b)) and random contributions (red in (b).

which are used to represent the reference signals are systematically removed from observation signals in order to produce domain-invariant signals, as illustrated in Figure 2.

Additionally, the effects of varying speeds must be considered. Order Tracking is often used to resample the signal from the time domain to the order domain. However it requires information on the instantaneous rotating speed of the machine, which is often not available in industrial scenarios.

Consequently, we use the Fourier atoms from the sparse decompositions in order to estimate the instantaneous rotating speed without the need for additional hardware using the ridge tracking technique proposed in (Iatsenko, McClintock, & Stefanovska, 2016). The signal is then resampled from the time domain to the order domain, so that all domains share the same rotating speed reference.

4. Experimental verification

In this study, the Machinery Fault Simulator from SpectraQuest was used as test rig (pictured in Figure 3). It consists of an 3-phase 1HP motor, a main shaft with two Rexnord ER12K bearings and a gearbox linked to the main shaft by a double groove rubber belt. Three different couplings between the motor and the shaft are available (rigid, jaw, beam). A magnetic brake on the gearbox can be used to manually vary the load applied on the gearbox. The motor's speed can vary from 0 to 6000 RPMs.

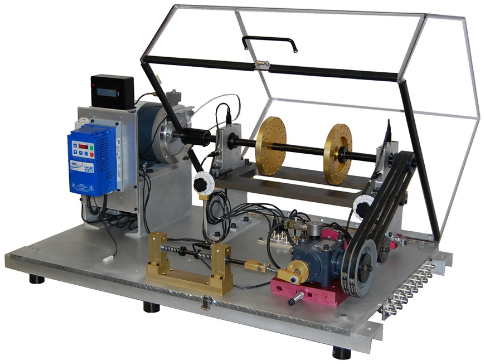

Figure 4. The SpectraQuest test bench

Table 1. Considered faults

Defect	Type	Severity
Bearing	Inner ring	High
	Outer ring	High
Rotor	Static unbalance	Low
	Static unbalance	High

The vibration signals are acquired using three IFM VSA005 accelerometers sampling at 25.6 kHz, placed on the rightmost bearing housing. A high sampling rate is indispensable as some faults occur at high frequencies. Several artificial defects representative of most naturally occurring faults are introduced as summarized by Table 1.

In the present investigation, the test bench was employed to generate datasets across five distinct domains. Each domain is characterized by a specific speed curve that exemplifies an acceleration and deceleration cycle—commonly referred to as coast-up and coast-down phases. Such cycles are emblematic of the fluctuating operational conditions frequently encountered within industrial environments.

The domain shift problem is illustrated in Figure 5. A lightweight one-dimensional Convolutional Neural Network (1D-CNN) was used, based on the architecture described in Table 4, was trained on a single domain. The 1D-CNN is recognized as the state-of-the-art architecture (Borghesani, Herwig, Antoni, & Wang, 2023) for intelligent vibration-based fault diagnosis. Despite the impressive performance for working regimes of 1500 RPMs, the model accuracy drops significantly when the rotating speed varies.

Subsequently, five transfer tasks were defined, each depicted in Table III. The construction of these tasks allows defining actual transfer scenarios in the presence of varying working conditions.

The subsequent discussion will illustrate how the suggested pre-processing technique enhances the generalization capabilities of the CNN model, without requiring the adoption of

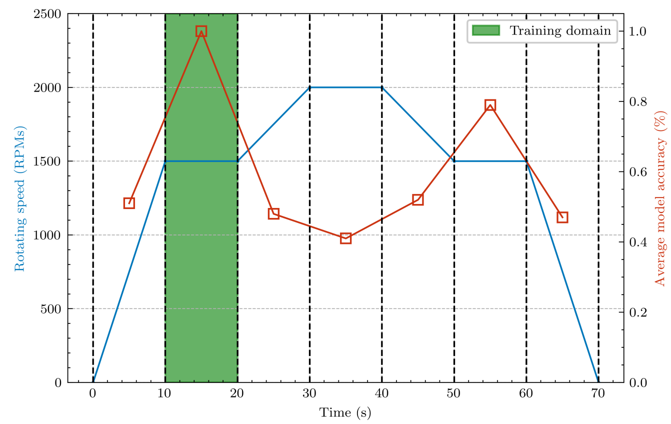

Figure 5. The domain shift problem: model accuracy decreases significantly when used on working conditions not represented in the training data

Table 2. Domains

Domain	Speed (RPM)
A	0 to 1500
B	1500
C	1500 to 2500
D	2500
E	2500 to 1500
F	1500
G	1500 to 0

Table 3. Cross-domain diagnosis tasks

Task	Source domain	Target domain
1	B	A
2	B	C
3	B	D
4	B	E
5	B	F
6	B	G

a more complicated model.

Table 4. 1D CNN Architecture

Layer Type	In. Ch.	Out. Ch.	Kernel/Stride/Size
Conv1d	1	3	Kernel=100, Stride=1
MaxPool1d	-	-	Kernel=8, Stride=8
Conv1d	3	3	Kernel=50, Stride=1
MaxPool1d	-	-	Kernel=5, Stride=5
Linear (FC1)	195	32	-
Dropout	-	-	p=0.5
Linear (FC3)	32	5	-

5. Results and discussion

The model was trained in each task with 120 samples per source domain, with a sample being a 3125-long vibration signal in 10 different runs. The lambda parameter was set empirically to 1.2, the learning rate to 0.001, the number of epoch to 200. The early stopping strategy was employed to obtain a satisfying trained model. Note that the model itself is not the focus of the present study, it is merely used to demonstrate the generalization capabilities increase enabled by the proposed method.

The accuracies on unseen test domains with and without the preprocessing employed are then compared. It is important to note that whether with or without the preprocessing runs, the target domains were never included in the training data, meaning that the inference is performed on never-seen-before domain distributions.

The diagnosis results on each of the cross-domain diagnosis tasks are shown in Figure 4. Where it can be seen that the proposed pre-processing method increases the cross-domain accuracy of the model. The task 4 yields a diminished increase because the rotating speed of the target domain is identical to the source domain, showing that the proposed method does not decrease the adequate performance of in-distribution classification performance of modern models.

It must also be noted however that the first and sixth task's accuracy are not improved by the proposed method as very low decreasing speed carry very little energy and thus very little information, making it difficult to apply the proposed preprocessing scheme.

This study addressed the common issue of 'domain shift' caused by changes in a machine's operational environment that often lead to errors in machine fault detection by sophisticated computer models. The proposed approach sought to simplify the diagnosis process by filtering out the environmental noise from the signals machines give off, focusing in on the genuine indicators of malfunctions.

To validate the proposed technique, a test bench that simulates a variety of operational conditions and failures machines might encounter in real-world scenarios was utilized. Across

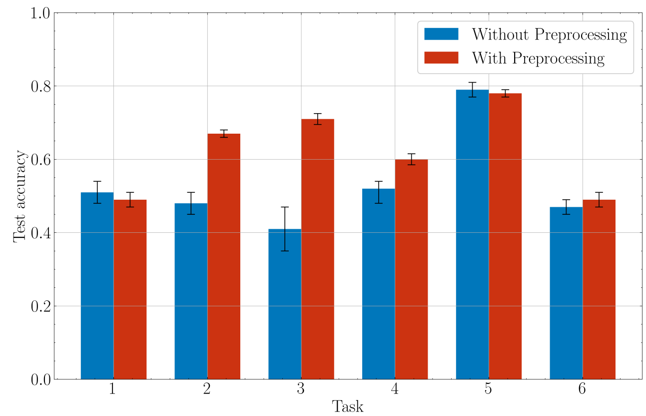

Figure 6. The effects of the proposed preprocessing method on the test accuracy of the model

five different domains, representing a range of typical industrial settings, our results indicate that our method, which employs a simple decision model with few parameters, was capable of identifying machine faults with an efficacy comparable to the more complex, state-of-the-art models currently in use.

6. Conclusion

In conclusion, this paper has presented a preprocessing technique that utilizes sparse representation to extract the domain-agnostic diagnosis information of machinery health signals, thereby significantly reducing the interference of domain-specific noise. The proposed method has been validated through a series of transfer tasks across different domains, revealing a significant improvement in model generalization without the necessity of resorting to complex neural network architectures.

On top of the generalization improvements, the proposed scheme use physically interpretable features which makes it easier to understand the output of the simple lightweight model employed here.

The study's limitations also open up new avenues for research, particularly in the domain of signal acquisition under extremely low-energy conditions. Addressing the shortfall in task 1 and 5 performance, where low decreasing speed results in signals with minimal information content, remains a challenge for future investigation.

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