Deep One-Class Method for Helicopter Anomaly Detection based on Cyclic Spectral Analysis

Normal Paper ☒
Student Paper ☐
Young Engineer Paper ☐

Chenyu. Liu [1,2] and Konstantinos. Gryllias [1,2]

[1] *Department of Mechanical Engineering, KU Leuven, Celestijnenlaan 300, Box 2420, 3001 Leuven, Belgium*
[2] *Dynamics of Mechanical and Mechatronic Systems, Flanders Make*

Abstract

An unsupervised Deep Support Vector Data Description model is proposed combining deep Convolutional Neural Network with SVDD for helicopter anomaly detection. The method uses 2D representations from cyclic spectral analysis as inputs, including Cyclic Spectral Correlation and Cyclic Spectral Coherence. A helicopter vibration dataset provided by Airbus SAS is used to test the proposed method, and the detection results prove its efficiency with high detection accuracy. Results from various feature extractors of the Deep SVDD are analyzed. Comparative analysis is also carried against reconstruction-based deep learning methods.

Keywords: helicopter anomaly detection, cyclic spectral analysis, deep learning, support vector data description, Deep SVDD

Introduction

Improving the reliability of helicopters meanwhile reducing the economic costs remains a longstanding challenge for the aviation industry. One aspect that attracts intense study and investment is substituting the periodic maintenance operations with Condition-based Maintenance (CbM) strategies. In contrary to the preventive examinations, CbM aims to use in-time monitoring information to schedule the maintenance. Therefore, an automated, efficient, and accurate anomaly detection system is of great importance for the CbM of an individual helicopter as well as the entire helicopter fleet.

In order to detect the anomalies, modern helicopter health management system leverages various sensors to collect in-flight information. These sensory measurements exist in extreme amount, complexity, and diversity but contain anomalous data indicating critical incidents on components. Classic data-driven anomaly detection methods utilize signal processing methods, such as spectrum analysis [1], time-frequency analysis [2], cyclic spectral analysis [3, 4], to construct engineer features as health indicators. However, these features always fail to accurately discriminate the anomalous in practical applications.

With the development of Artificial Intelligence (AI), nowadays, Machine Learning (ML) and Deep Learning (DL) methods have been extensively adopted in data-driven anomaly detection. Comparing to classic detection methods, ML and DL models are able to extract more discriminative features, which significantly improves the detection accuracy. In the past years, several DL tools has been proposed for anomaly detection tasks, such as autoencoder [5], Long Short-Term Memory (LSTM) network [6], Generative Adversarial Network (GAN) [7], and Variational Autoencoder (VAE) [8]. They provide promising results in rotating machinery anomaly detection cases, but the high demand from industry is provoking researchers to pursue detection models with higher accuracy.

Support Vector Data Description (SVDD) is an ML method used as a one-class classifier to serve anomaly detection tasks [9]. It utilizes healthy samples to construct a hyper-sphere feature space as a detection threshold. Recently, SVDD is extended as Deep SVDD, which exploits the powerful hierarchical feature extraction ability of deep neural networks [10].

The authors previous research [11] has proved the effectiveness of combining indicators from cyclic spectral analysis with SVDD method. In this paper, the method will be extended with Deep SVDD model. A Deep SVDD model is proposed using Cyclic Spectral Coherence map as the input for helicopter anomaly detection. The methodology is applied, tested and evaluated on a helicopter vibration dataset. Experimental results show that the proposed method is able to reach high anomaly detection accuracy, which indicates its promising potential in industrial application.

Theories

Cyclic spectral analysis

The vibration of rotating mechanical components usually performs cyclostationarity, which is a stochastic process caused by systematic periodicities. When a defect is generated during machinery operation, it usually presents as a series of repetitive shocks modulated by frequencies from other components within the cyclic transient signatures. Cyclostationarity can be defined based on the orders of moments. The first-order cyclostationarity (CS1) is the statistical mean related to the components phase-locked with rotor speed, therefore contains the characteristics from shaft misalignments, imbalances, or flexible coupling [3]. The second-order cyclostationarity (CS2) signature can reveal the hidden periodicity related to the shaft speed with the autocorrelation function. It has been used in the diagnostics of the rotating components not completely phase-locked with the rotor speed [12].

Cyclic Spectral Correlation (CSC) is a tool for the spectral analysis of cyclostationary signals using the autocorrelation function of two frequency variables, i.e., the cyclic frequency related to the modulation and the spectral frequency related to the carrier. Therefore CS1 and CS2 signals can be described in the frequency-frequency domain based on the correlation distribution:

$$CSC(\alpha, f) = \lim_{W\to\infty} \frac{1}{W} E\{F_W[x(t)]F_W[x(t+\tau)]^*\} \tag{1}$$

where $x(t)$ represents the time signal over a time duration W, and τ is the time-lag. E is the ensemble average operator, and F stands for the Fourier transform. CSC leads to a bi-variable map with the cyclic frequency α and the spectral frequency f. The normalization of the CSC map between 0 and 1 can reduce the uneven distributions, which leads to the Cyclic Spectral Coherence (CSCoh) as follows:

$$CSCoh(\alpha, f) = \frac{CSC(\alpha,f)}{\sqrt{CSC(0,f)+CSC(0,f-\alpha)}} \tag{2}$$

Both CSC and CSCoh are effective tools to reveal the masked, hidden characteristics within the cyclostationary signals. CSC is more used for trace the fault trending, but CSCoh can better detect the anomalies from the vibrations.

Unsupervised deep One-Class classification

Support Vector Data Description (SVDD) method was proposed as a One-Class (OC) anomaly detection method. It projects the data samples to a hyper-sphere feature space. By minimizing the volume of the sphere, it can separate the anomalies from normal data samples. For the input data space $\{x_1, x_2, \dots, x_n\} \in \mathrm{X}$ and the output feature space $\phi_k(x_i) \in \mathrm{H}_k$, the objective function of the mapping $\mathrm{X} \rightarrow \mathrm{H}_k$ with kernel k can be described as follows:

$$Y(R,a) = \min R^2 + \frac{1}{\upsilon n}\sum_{i=1}^{n} \xi_i$$
$$s.t.\ \|\phi_k(x_i) - a\|^2 \leq R^2 + \xi_i \qquad \forall i, \xi_i \geq 0 \tag{3}$$

where a is the center of the sphere and R is the radius. ξ_i is the slack variable which gives a flexible boundary of the sphere, and $\upsilon \in (0,1]$ is the penalty parameter related to the proportion of rejected outliers. Eqn. 3 can be further transformed to a dual problem solved by kernel function-based method [9].

When applying the classic OC-SVDD in anomaly detection cases, the inputs are usually the health indicators, which require expert knowledge to extract from the raw measurements. On the one hand, this increases the complexity of the anomaly detection procedure with an extra indicator selection step. On the other hand, the detection accuracy highly relies on the quality of these indicators. In order to exploit the strong non-linear representation learning ability of networks, an unsupervised deep OC anomaly detection method, Deep SVDD, has been proposed [9]. Instead of directly using indicators to train the SVDD hyper-sphere, Deep SVDD uses the deep neural network to extract smart features from the inputs. The schematic of Deep SVDD is shown in Fig. 1.

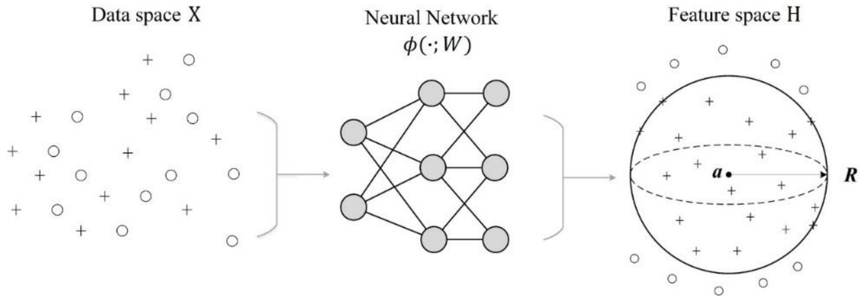

Fig. 1: The schematic of Deep SVDD.

Following the SVDD, the aim of the Deep SVDD is to minimize the volume of the data-enclosing sphere and jointly learn the weights of the network. Consider a neural network $\phi(\cdot; W)$: $\mathrm{X} \rightarrow \mathrm{H}$ with weight W, the optimization function of Deep SVDD can be described as follows:

$$Y_1(R,a,W) = \min R^2 + \frac{1}{\upsilon n}\sum_{i=1}^{n} \max\{0, \|\phi(x_i; W) - a\|^2 - R^2\} + \frac{\lambda}{2}\sum_{l=1}^{L} \|W^l\|_F^2 \tag{4}$$

With a sphere characterized by the center a and radius R, the minimization of R^2 will lead to the minimum volume. The second term of Eqn. 4 is the penalty from the points outside the boundary, where υ is acting the same role as in Eqn. 3. In the third term, W^l represents the weight for the l-th layer, and $\|\cdot\|_F$ is the Frobenius norm. $\lambda > 0$ is a hyper-parameter to regulate the weight decay.

Deep SVDD can use various forms of representations from the raw measurements as inputs for smart feature extraction instead of using the engineering health indicators. The multi-layered network structure makes it suitable for learning representations from hierarchical data like 2D images.

Methodology

Since the CSC and CSCoh approaches have the strong power to reveal the hidden periodic information from the cyclic vibration signals, it has been utilized to generate 2D representations as the inputs for smart feature extraction within deep learning models [12]. In order to make a high accuracy detection method, this paper proposes an unsupervised anomaly detection model, combining the CSC/CSCoh method with the Deep SVDD model, as illustrated in Fig. 2.

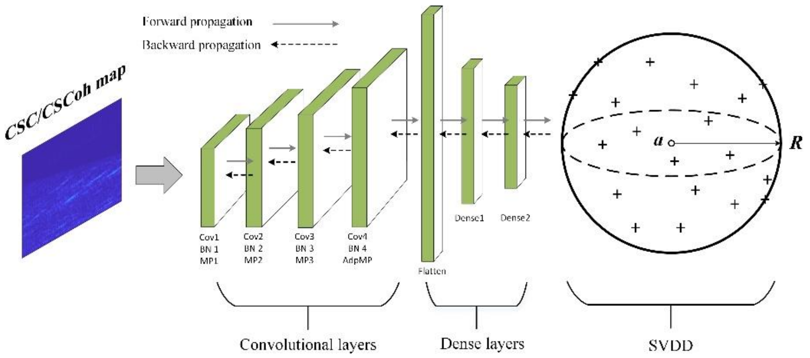

Fig. 2: The proposed CSCoh-based Deep SVDD method.

The raw vibration signals from the healthy training dataset are firstly transformed to frequency-frequency 2D representations using CSC/CSCoh, and then sent to the Deep SVDD model. The feature extractor of the Deep SVDD is composed by four Convolutional Neural Network (CNN) blocks, and each block contains one convolution layer (Cov: kernel size=3), one maxpooling layer (MP: kernel size=2), and one batch normalization layer (BN). An adaptive maxpooling layers (AdpMP) is added to the last CNN block. Two dense layers follows the flatten layer with size 1024-128 using ReLU activation. For the hyper-sphere SVDD part, the hyper-parameter λ is set to 0.1 and the trade-off proportion parameter is set to 0.01.

Experiment

Experimental dataset

A helicopter vibration dataset from Airbus SAS is used for the experiment [14]. Each sample from the dataset contains vibration signals gathered from accelerometers mounted on different positions of helicopters with a sampling frequency of 1024 Hz. The signals are grouped in two sub-sets, including the training dataset with 1677 samples from normal flights and the validation dataset with 594 samples from both normal and abnormal flights.

Comparative analyse methods

In order to compare different cyclic spectral analysis approaches, both the CSC and CSCoh maps are used as the inputs of the proposed Deep SVDD model. Four different CNN-based network architectures are adopted to compare the feature extraction efficacy, including the proposed four-block CNN model, the AlexNet, the ResNet, and the LeNet. Furthermore, two reconstruction-based anomaly detection methods, i.e., GAN, and VAE, are also used on the CSC and CSCoh maps to compare the results.

Results

The anomaly detection results are evaluated by True Positive Rate (TPR), False Positive Rate (FPR), F1-score, and Area Under the receiver operating characteristics Curves (AUC). The anomaly detection results from different Deep SVDD models with both CSC and CSCoh as inputs are listed in Table 1. It can be found that, in general, the CSCoh inputs perform better than the CSC. The highest F1-score yields 0.91, which is found from the proposed CNN-based Deep SVDD with CSCoh inputs.

Table 1: Anomaly detection results of Deep SVDD models.

	CSC				CSCoh			
	CNN	AlexNet	ResNet	LeNet	CNN	AlexNet	ResNet	LeNet
TPR	0.82	0.89	0.42	0.74	0.91	0.85	0.85	0.80
FPR	0.02	0.09	0.20	0.00	0.00	0.04	0.10	0.12
F1-score	0.87	0.76	0.59	0.81	0.91	0.80	0.66	0.82
AUC	0.86	0.74	0.80	0.82	0.90	0.82	0.81	0.82

The results from reconstruction-based methods are shown in Table 2. The VAE model gets higher F1-score and AUC value than the GAN model for both inputs. However, compared to the Deep SVDD method, both the GAN and the VAE model yields lower detection accuracy. On the other hand, it should be noticed that, for the GAN model, the CSC inputs get better performance than the CSCoh inputs, which behave differently from the other methods.

Table 2: Anomaly detection results of reconstruction-based methods.

	CSC		CSCoh	
	GAN	VAE	GAN	VAE
TPR	0.70	0.83	0.65	0.85
FPR	0.00	0.12	0.02	0.04
F1-score	0.76	0.78	0.73	0.84
AUC	0.79	0.80	0.70	0.84

Conclusions

This paper proposed an unsupervised deep learning approach for helicopter anomaly detection based on cyclic spectral analysis. A CNN-based Deep SVDD model is constructed with CSC and CSCoh maps as inputs. The methodology is applied on a helicopter vibration dataset from Airbus, and experimental results show that the method can reach high detection accuracy with promising potential for industrial application.

Acknowledgements

The authors would like to acknowledge the support of the China Scholarship Council, the Flemish Government under the "AI Flanders" programme, and Flanders Make Strategic Basic Research project: DGTwin Prediction.

References

1. Randall, R. B., and Antoni, J., "Rolling element bearing diagnostics—A tutorial." *Mechanical Systems and Signal Processing* 25.2 (2011): 485-520.

2. Chandra, N. H., and Sekhar, A. S., "Fault detection in rotor bearing systems using time frequency techniques." *Mechanical Systems and Signal Processing* 72 (2016): 105-133.

3. Antoni, J., "Cyclic spectral analysis of rolling-element bearing signals: Facts and fictions." *Journal of Sound and Vibration* 304.3-5 (2007): 497-529.

4. Mauricio, A., and Gryllias, K., "Cyclostationary-based multiband envelope spectra extraction for bearing diagnostics: The combined improved envelope spectrum." *Mechanical Systems and Signal Processing* 149 (2021): 107150.

5. Liu, H., et al. "Fault diagnosis of rolling bearings with recurrent neural network-based autoencoders." *ISA transactions* 77 (2018): 167-178.

6. Galati, F., Wenyi, W., and Bradley B., "Gear-bearing fault detection based on deep learning." *AIAC18: 18th Australian International Aerospace Congress* (2019).

7. Jiang, W., et al. "A GAN-based anomaly detection approach for imbalanced industrial time series." *IEEE Access* 7 (2019): 143608-143619.

8. San, G., et al. "Deep variational auto-encoders: A promising tool for dimensionality reduction and ball bearing elements fault diagnosis." *Structural Health Monitoring* 18.4 (2019): 1092-1128.

9. Tax, M. J., and Robert, D., "Support vector data description." *Machine learning* 54.1 (2004): 45-66.

10. Ruff, L., et al. "Deep one-class classification." *International conference on machine learning*. PMLR, (2018).

11. Liu, C., and Gryllias, K., "A semi-supervised support vector data description-based fault detection method for rolling element bearings based on cyclic spectral analysis." *Mechanical Systems and Signal Processing* 140 (2020): 106682.

12. Antoni, J., "Cyclostationarity by examples." *Mechanical Systems and Signal Processing* 23.4 (2009): 987-1036.

13. Chen, Z., et al. "A deep learning method for bearing fault diagnosis based on cyclic spectral coherence and convolutional neural networks." *Mechanical Systems and Signal Processing* 140 (2020): 106683.

14. Garcia, G. R., et al. "Time series to images: Monitoring the condition of industrial assets with deep learning image processing algorithms." *arXiv preprint* arXiv:2005.07031 (2020).