Investigating Noise Reduction in Signal Analysis in Rotary Machines Fault Diagnosing by Neural Network

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ABSTRACT

Fault diagnosis of mechanical systems is of special importance for better system performance as well as its protection. In this work, a rotary machine laboratory system is used to generate signals. The obtained data are placed in the pre-processing process. In this article, to improve the performance of signal analysis, the combined analysis methods using signal features and Kalman filter are proposed. First, the Kalman filter is used to reduce the signal noise. In the following, for signal pre-processing, the features of the signal in the time domain and frequency domain are suggested, which have been used as one-dimensional signal pre-processing. In the following, several neural networks such as support vector machine, multilayer perceptron, and convolutional neural networks have been used to analyze the obtained features. To check the results, the data is divided into training data and validation data. Accuracy results for validation data are examined in different methods. The results indicate the better performance of the AlexNet convolutional neural network in the presence of the Kalman filter noise reduction. In this case, this network has reached an average of 96.1% accuracy for validation data, which has been improved compared to other classifiers and fault diagnosis without noise reduction.

KEYWORDS

Fault diagnosis, noise reduction, Kalman filter, neural network, signal processing.

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1. Introduction

Today, intelligent fault diagnosis has become a crucial aspect of the mechanical system. The faults can lead to severe damage and complications. Hence, early detection of defects in the early stages is of paramount importance. In this context, the processing of vibration signals for rotary mechanical systems can prove to be highly effective in fault detection before system failure. Here is a brief summary of the tasks involved in detecting faults in rotary machinery.

Junior et al. employed signal pre-processing techniques for fault diagnosis in rotating machinery [1]. Zakizadeh et al. utilized vibration analysis in conjunction with support vector machine algorithms to diagnose faults in the rotary blower systems of Alstom locomotives [2]. Shekarzadeh et al. introduced an independent component analysis and particle batch optimization for diagnosing defects in centrifuge bearings [3]. Several noise reduction methods, including the integration of Kalman filtering with signal analysis techniques, yield promising results in this field [4].

This article presents a novel approach that combines feature extraction and the Kalman filter noise reduction for fault diagnosis. Features are extracted from clean signals in the time and frequency domains. The preprocessed data are utilized as training data for different networks. By utilizing the capabilities of neural networks, the article aims to enhance the accuracy and effectiveness of fault diagnosis.

2. Experimental Data Collection

In this study, vibration data from a rotary machine is utilized. Figure 1 illustrates the configuration of the system, which consists of an alternating current motor connected to a rod mounted on three bearings. The system also includes discs that can cause the disk to become unbalanced. Two sensors are placed on the first and second bearings from the right side to record signal data. The bearing locations are indicated in Figure 1.

To capture validation signals from this rotary machine, three types of faults are introduced: bearing ball defects, rod imbalance, and bearing outer ring defects. Additionally, signals are recorded in a healthy system state. To record the signals in various system states (both faulty and healthy), the motor feeding frequency is varied between 8 and 30 Hz in 2 Hz increments and it has a rated speed of 2825 rpm at a feeding frequency of 50 Hz and a power rating of 370 watts.

During data recording, the healthy system state is considered as the baseline. In the case of bearing ball failure, the defective bearing is placed in three different positions as depicted in Figure 1. Similarly, for the outer ring failure, the defective bearing is placed in three positions. As for rod imbalance, weights are added to each of the six discs mounted on the rotating rod. Overall, there are 13 system modes considering the general states of healthy and faulty systems. Data recording is done across 12 different motor feeding frequencies, resulting in a total of 156 primary data points. Each of these 156 primary data points includes two one-minute signals (due to the two sensors in the system) and four labels indicating the system state (healthy or faulty). The signals are recorded at a rate of 10,000 pulses per second.

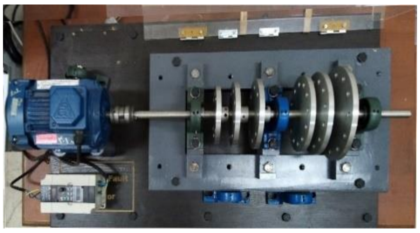

Figure 1: Laboratory rotating machine for data recording

A targeted random method is employed to split the data into training and validation sets. About 20% of the 156 data points are allocated as validation data. In each case of system mode, 2 or 3 validation data points are randomly selected. To ensure robustness in the analysis, the data division is performed five times, allowing for better analysis of the results.

3. Feature Extraction

To analyze the signals, feature extraction is performed in both the time and frequency domains. Fourteen features are extracted in the time domain [5], while nine features are extracted in the frequency domain [6].

In the time domain, the signal is directly processed for feature extraction. In the frequency domain, prior to feature extraction, the signal spectrum must be obtained. The signal can be transformed to the frequency domain by Fast Fourier Transform (FFT).

4. Evaluation of Neural Network Training Results

As previously explained, 23 features are extracted from each signal, resulting in 46 numerical values recorded for each data point. Therefore, the input data dimensions for the MLP and SVM neural networks are 125 x 46, representing 125 data points out of the total 156 (considered as training data). Additionally, for CNN models with Inception and AlexNet architectures, the input data is reshaped into a 2D format to enable analysis with 2D convolutional tools. Consequently, the last feature is omitted, and the remaining 45 features are arranged as a 5 x 9 matrix, resulting in input dimensions of 125 x 5 x 9 for the CNN network.

To assess the impact of signal noise reduction, since the variance of the system noise is unknown, trial and error method is used to set different values (0.25, 0.5, and 0.75) for the measurement noise covariance *R*. Therefore, the noise of desired signal is reduced in three modes, while a mode without noise reduction is also considered during feature extraction. Considering the influence of data division on the neural network training results, each classifier is trained in five different data divisions and mean value of the results are shown in table 1. The results indicate that the AlexNet network performs better than the others

Table 1: The mean of the validation data accuracy for each classifier for each Kalman noise reduction mode

	$R = 0.25$	$R = 0.5$	$R = 0.75$	Not denoise
Classifier	Mean	Mean	Mean	Mean
SVM	0.935	0.942	0.922	0.910
MLP	0.948	0.948	0.935	0.955
Inception	0.942	0.948	0.935	0.948
AlexNet	**0.961**	**0.961**	**0.955**	**0.955**

To compare the effect of noise reduction achieved by the Kalman filter, the mean and variance of the accuracy for all validation data are calculated for each noise reduction mode in Table 2. It is observed that the best accuracy for evaluation data is obtained when the measurement noise covariance *R* is set to 0.5. Consequently, the accuracy is improved compared to the mode without noise reduction. The accuracy results for validation data show less variation when the measurement noise covariance is set to $R = 0.75$. Finally, based on tables 1 and 2, it can be concluded that the AlexNet neural network yields the best results in reducing Kalman filter noise with an *R* value of 0.5.

Table 2: The mean and variance of accuracy of the validation data for all classifiers for each Kalman noise reduction mode

Noise reduction mode	Mean	Variance
$R = 0.25$	0.947	0.0012
$R = 0.5$	**0.95**	0.0014
$R = 0.75$	0.937	**0.009**
Without Noise reduction	0.942	0.0017

5. Conclusions

The objective of this study was to examine the influence of noise reduction through the utilization of the Kalman filter on fault detection in the rotary machine. The laboratory data underwent noise reduction using the Kalman filter in various modes. Subsequently, features were extracted from the signals. Various neural networks, including SVM, MLP, Inception, and AlexNet, were trained using these datasets.

In the investigation of signal noise reduction, the AlexNet network consistently outperformed other methods. The best accuracy results were obtained with the measurement noise covariance $R = 0.5$. The AlexNet network achieved an accuracy of 96.1% with $R = 0.5$. Comparing the average results for different noise reduction modes across all classifiers, an accuracy of 95% was achieved with a measurement noise covariance of $R = 0.5$, which showed improvement compared to the mode without noise reduction.

Future work could involve optimizing the covariance values of *Q* and *R* in the Kalman filter for signal noise reduction. Since the noise covariance of the recorded signals is unknown, these values can be determined through optimization methods to further enhance the performance of the system.

6. References

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