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Multiple Engine Faults Detection Using Variational Mode Decomposition and GA-K-means

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Abstract

As a critical power source, the diesel engine is widely used in various situations. Diesel engine failure may lead to serious property losses and even accidents. Fault detection can improve the safety of diesel engines and reduce economic loss. Surface vibration signal is often used in non-disassembly fault diagnosis because of its convenient measurement and stability. This paper proposed a novel method for engine fault detection based on vibration signals using variational mode decomposition (VMD), K-means, and genetic algorithm. The mode number of VMD dramatically affects the accuracy of extracting signal components. Therefore, a method based on spectral energy distribution is proposed to determine the parameter, and the quadratic penalty term is optimized according to SNR. The results show that the optimized VMD can adaptively extract the vibration signal components of the diesel engine. In the actual fault diagnosis case, it is difficult to obtain the data with labels. The clustering algorithm can complete the classification without labeled data, but it is limited by the low accuracy. In this paper, the optimized VMD is used to decompose and standardize the vibration signal. Then the correlation-based feature selection method is implemented to obtain the feature results after dimensionality reduction. Finally, the results are input into the classifier combined by K-means and genetic algorithm (GA). By introducing and optimizing the genetic algorithm, the number of classes can be selected automatically, and the accuracy is significantly improved. This method can carry out adaptive multiple fault detection of a diesel engine without labeled data. Compared with many supervised learning algorithms, the proposed method also has high accuracy.

Introduction

The diesel engine is an essential power source in modern production and life, especially in transportation, power generation, manufacturing, and other related fields [1]. With the increasingly severe energy and environmental problems, the requirements for power performance and emission of diesel engines are becoming higher. Improving intake efficiency and compression ratio and fine control of injection time and quantity are essential measures to meet this requirement. This also leads to more complex mechanical structures and higher failure probability [2]. Therefore, the engine faults detection method research plays a critical role in improving safety and reducing accidents.

At present, there are many fault detection methods. The first is detecting specific signals and setting fault thresholds according to expert knowledge [3]. Sumanth et al. used an invasive differential pressure sensor to detect the disconnection of the hose downstream of the GPF [4]. This method is stable and straightforward, but it is usually invasive and aimed at single fault diagnosis. The second is the model-driven fault diagnosis method [5]. Chowdhury et al. predicted the lead mismatch fault of helical gear mounted on balance shaft through dynamic modeling [6]. This method has high accuracy, but the actual conditions of machinery are complex and noisy, which leads to the difficulty of dynamic modeling. The third is the data-driven method, which is also used in this paper. Zhang et al. proposed a generalized logarithm penalty to improve the reconstruction accuracy of sparse expression then raise the accuracy of bearing fault diagnosis [7]. This method usually uses non-invasive signals such as sound and vibration to diagnose various faults. The problem is that it needs a lot of data and a complex signal processing process.

Generally, it is not effective to diagnose the original signals directly using the pattern classification methods [8]. High dimensional features can be extracted through signal decomposition, and the pattern classification methods can achieve better results [9]. Fourier transform and short-time Fourier transform (STFT) are commonly used to obtain basic frequency domain features [10, 11]. The intrinsic mode functions and fault-sensitive information can be obtained through empirical mode decomposition (EMD) [12], wavelet transform (WT) [13], variational mode decomposition (VMD) [14], etc., table is the average of 5 calculations. For abnormal fuel supply, abnormal common rail pressure, and abnormal valve clearance, the accuracy of the proposed method is 100%, 97.3%, and 94.4%, respectively. Compared with the results in Fig.8, the accuracy is slightly improved because the number of single classifications is reduced. The results show that the accuracy of the proposed method is improved compared with unsupervised K-means and EM. Without using labeled data, the accuracy of the proposed method can be higher than the classical supervised learning algorithms such as SVM and BPNN. Since the GENCLUST + + is also an unsupervised method without training error, its robustness is good. Feature selection reduces data redundancy and the possibility of data overfitting. However, the accuracy of BPNN and SVM methods improves with more and better training data, which is not achieved by the proposed method.

In addition, the proposed method can be extended to different engines. The calculation process of frequency domain energy distribution needs to be performed to determine the new proper *K* and initial center frequencies. The results show that the proposed method has a certain application prospect in engine fault detection.

Conclusion and Discussion

Conclusion

This paper researched a novel method to detect multiple engine faults based on vibration signals. The main conclusions are:

1. RVMD is introduced to study the frequency domain energy distribution of engine vibration signals, and six main frequency components of 0.2 kHz, 1.4 kHz, 1.9 kHz, 2.4 kHz, 4.8 kHz, and 6.9 kHz are obtained. The α is optimized according to the SNR of decomposition. Finally, the decomposition effect of VMD is improved by optimizing K, α, and initial center frequencies.

2. The IMFs obtained from VMD are used to calculate five kinds of parameters to describe the features of fault signals. Redundant feature parameters will reduce the efficiency and accuracy of classification. The stepwise greedy correlation-based feature selection is used to obtain the best feature subset.

3. VMD-GENCLUST + + is used to diagnose eight kinds of engine fault data, and the accuracy is 96.9%. Compared with other methods, the proposed method without labeled data can achieve similar or even higher diagnostic accuracy with supervised learning algorithms such as SVM and BPNN.

Discussion and Outlook

There is much research that should be done in the future:

1. VMD using fixed *K* value is challenging to meet the decomposition requirements of various kinds of signals, so it needs to make a choice between adaptive decomposition and unified feature dimension. It is hoped that a balanced approach can be developed in the future.

2. GENCLUST + + has low efficiency in classifying high-dimensional data. The genetic algorithm will be optimized to improve efficiency in the future, especially in the initialization stage.

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Definitions/Abbreviations

GA - Genetic Algorithm
SNR - Signal-to-Noise Ratio
EMD - Empirical Mode Decomposition
WT - Wavelet Transform
VMD - Variational Mode Decomposition
EEMD - Ensemble Empirical Mode Decomposition
BPNN - Back Propagation Neural Network
SVM - Support Vector Machine
IMF - Intrinsic Mode Function
RVMD - Recursive Variational Mode Decomposition
CFS - Correlation-based Feature Selection
EM - Expectation-Maximization.

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