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Comparisons of different deep convolutional neural network and machine learning based methods on gearbox fault diagnosis using small dataset

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Abstract

Modern industry prioritizes condition monitoring and problem diagnostics due to safety and quality standards. Modern gearboxes, one of the most common components, break under intense operating conditions and require problem detection. Vector assessment and vibration signal analysis have successfully used deep learning to extract representative information and sensitive features from raw data to diagnose gearbox faults. Deep learning for mechanical diagnostics is relatively restricted, and few research have compared feature learning with varied data sources. This study uses vibration signal temporal data to train a convolutional neural network (CNN) using multiple architectures. UoC gearbox data verifies the technique against seven typical intelligent ways. Adaptive learning from temporal data enhances diagnostic accuracy.

Introduction

In this paper, we used End-to-end stacked CNN with several architectures to learn features using limited time do-main data, raw time and frequency of the data, and identify gearbox health issues. We designed multiple CNN model architectures with different hyper-parameters to find the best model combination. As comparisons, used angle-frequency domain synchronous analysis (AFS) (Huang HB) [1] followed by Support Vector Machine (SVM) classification and six intelligent approaches: SVM with RBF Kernel, Multi-Layer Perceptron (MLP), K-Nearest Neighbors (K-NN), Logistic Regression, and random forest (RF). The selection of several critical CNN parameters is described, and the performance of the proposed approach and CNN detection results with different configurations are compared in experiments.

Material and Method

This section describes the suggested gear failure diagnosis approach. which may be separated into three parts: first, the raw time-domain vibration data was received from the University of Connecticut gear fault datasets, which were recorded at 20 kHz. The input shaft pinions were examined for nine gear conditions, including healthy, missing tooth, root fracture, spalling, and chipping tip, each with five severity degrees. The vibration signal is directly fed into the enhanced CNN model for back-propagation training. All datasets were divided into nine categories (one health status and eight fault states) to assess performance. Second, our trained CNN extracts representative features from fresh defect raw data. The second comparative method is angle-frequency domain synchronous analysis (AFS) [2] followed by Support Vector Machine (SVM) classification of dense representative feature vectors.

Gearboxes may fail in several ways. Vibration signals from such a system indicate system health. This research uses a 2-stage gearbox with interchangeable gears [3].

Motors control gear speed. A magnetic brake's input voltage controls torque. 32-tooth pinion and 80-tooth gear on the first stage intake shaft. The second stage has a 48-toos pinion and 64-too gear. Gear vibration signaling monitors an accelerometer, while a tachometer measures input shaft speed. dSPACE can sample signals at 20 KHz (DS1006 Processor Board, dSPACE Inc., Wixom

As noted in Section above, each gear situation creates 208 vibration signals. In the input shaft, 9 gear defects—health, missing tooth, root fracture, spalling, and chip tips with five severity degrees are delivered to the pinion. Dynamic responses of a gear-driven angle-periodic system. The transmission system's spinning speed is expected to be constant since it's transient. Due to load disturbances, geometry tolerances, and motor control errors, this assumption is frequently wrong. Vibration signals in the original time domain are converted from time to angle with an equal angular increase in this study.

The University of Connecticut (UoC) [4] Gear one-dimensional original vibration data set was used to assess the one-dimensional-CNN. The dataset has 936 samples, but in our study, 208 signals are generated using the gearbox system for each gear condition. In the period of 4 gear rotations, 1872 angle-even samples are collected for each signal, corresponding to half of the original. To achieve the highest train and test accuracy, the first 208 samples are healthy, 209th - 313th samples are missing, and etc. Therefore, each sample is a tensor of (1872x1x3) dimension and the input tensor for each heal.

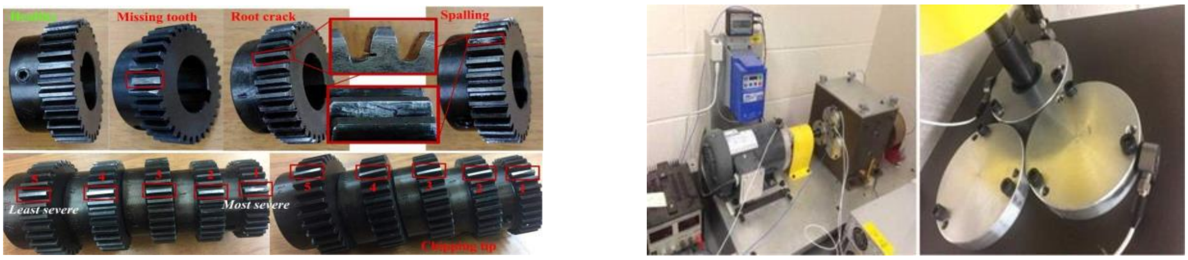

Figure 1. Experimental study gearbox

Results and Discussion

1. The case study findings in Table 1 demonstrate that the proposed method is successful at diagnosing gearbox problems, with the best testing accuracies of 100 percent and validation of 100 percent in this context. According to the experimental findings of CNN with different configurations, CNN with more layers has higher accuracy and a more stable outcome than CNN with fewer layers. In general, a bigger segment size can supply more specific information to CNN than a smaller one. However, increasing the segment size reduces the amount of data segments, which may have a detrimental impact on CNN training. As a consequence, segment size 1872 yields the best results. Although pooling may result in the loss of local information, in our situation, CNN with two pooling layers outperforms CNN with one pooling layer.
2. In comparison to AFS-SVM, the proposed approach not only outperforms it in terms of performance, but it also requires no pre-processing effort, time domain analysis in this case, making the proposed approach more unbiased in feature extraction and more easily applicable to other fault diagnosis practices. The proposed technique also yields excellent results in terms of robustness.
3. When comparing the performance of feature learning with manual feature extraction, feature learning with CNN produces much better results than manual feature extraction using Machine learning, with an increase in testing accuracy of roughly 10%. This outcome is highly associated with CNN's unique design, which can automatically extract representative information from raw data layer by layer and produce usable features in higher layers for classification. This benefit of CNN not only lowers the requirement for human labor and prior knowledge of signal processing and diagnostic methodologies for feature extraction, but it also adaptively adapts the learnt features to handle various fault diagnosis challenges.
4. While CNN performs better with feature learning, all of the models examined, including AFS-SVM, MLP, SVM, K- NN, LR, RF, and GNB, perform similarly with manual features. Table 4 clearly shows that End-to-end stacked CNN produces higher testing and validation accuracies than other comparison models for the same data type. However, when using manual features, all of the models show identical accuracies, indicating that CNN cannot produce much greater gains in defect identification than traditional approaches without the capacity to learn features.

Table 1. Classification results

Gear fault Diagnosis Method	Training Acc %	Testing Acc
% End-to-end stacked CNN (our model)	**100**	**100**
Learning features + AFS-SVM	87.48	86.57
manual feature + (SVM) with RBF Kernel	93.12	91.47
manual feature + (MLP)	96.33	96.27
manual feature + (K-NN)	91.52	81.60
manual feature + Random Forest	94.52	94.13
manual feature + Logistic Regression	68.74	70.40
manual feature + Gaussian Naive Bayes	93.79	94.40

Conclusion

This paper develops a One-Dimensional deep Convolutional Neural Network for deep feature extraction and Gear defect Classification. The suggested solution uses less data than AFS-SVM and machine learning and enables free adaptive feature extractions. The proposed End-To-End Convolutional Neural Network architecture has two sections: a pre-trained deep neural network that automatically extracts features from the input, and a fully connected stage for classification that must be trained. The UoC [5] datasets with Raw time data were used to validate the method, which achieved 100% accuracy with a small error rate. Finally, we compared it with AFS-SVM [6] and the most prominent machine learning methods for gear defect classification (Support Vector Machine, Multi-Layer Perceptron, K-Nearest Neighbors, Random Forest, Logistic Regression, and Gaussian Naive Bayes) using frequency domain training and testing data. Statistical feature extraction methods extracted meaningful characteristics from frequency domain data. Training and Testing Accuracy on performance measures of applicable ML algorithms is compared.

MLP (Multi-Layer Perceptron) had the maximum accuracy of 96.27 percent for dataset diagnosis of gear faults. It would be fascinating to identify faults in various gear defects with huge datasets and varied difficulties. Experiments demonstrate that the proposed method can learn characteristics and recognize gearboxes with various faults. Compared to manual feature extraction, the recommended method increases classification accuracy by 10% with less technical expertise and effort. At the same time, our model gets the maximum accuracy with Raw time domain data across all data sources, suggesting that the CNN model is better suited to learn features from vibration data in time domain, as shown in CNN-based vibration analysis. Deep learning for mechanical defect diagnoses is untested. Understanding deep learning generalization is crucial for future research.

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