Research on Virtual Measurement Method for Ship Rolling Bearing Faults Based on CNN-LSTM

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Abstract: *Rolling bearings are key components in the power transmission system of naval ships, and their operating status directly afects the reliability and safety of the ship power system. Aiming at the problems of complex operating environment, non-linear and non-stationary vibration signals, and weak early fault characteristics of naval ship equipment, this paper studies the virtual measurement method for rolling bearing faults of naval ships. A fault virtual measurement model fusing convolutional neural network (CNN) and long short-term memory (LSTM) network is constructed. The CNN is used to extract the local impactfeatures of vibration signals, and the LSTM network is adopted to model the temporal evolution law of fault features, so as to realize the end-to-end mapping from vibration signals to bearingfault status. An experimental dataset is built based on the vibration data of ship rotating machinery, and the modelperformance is verified through model comparison experiments, noise robustness tests and early fault detection experiments. The experimental results show that the proposed model outperforms the comparison models such as support vector machine (SVM), CNN and LSTM in terms offault diagnosis accuracy, anti-noise performance and early fault identification ability, with a diagnosis accuracy of92.1%. The research results demonstrate that the proposed method can achieve high-precision virtual measurement of the health status of key components in ship power systems.*

Keywords: *Virtual Measurement; Convolutional Neural Network; Long Short-Term Memory Network; Rolling Bearing; Fault Diagnosis*

1. Introduction

Rolling bearings are key components in ship power systems. In rotating machinery such as the main propulsion plant, auxiliary mechanical systems, and drive shafting, their operating conditions significantly affect the stability of power output and the safety of the ship system[1]. When ships operate for a long time in harsh sea conditions, variable working conditions, and complex vibration environments, bearings are prone to failures such as fatigue spalling, wear, and cracks. If these failures are not identified in a timely manner, the power system will suffer from abnormal vibration, and equipment failure may even occur[2-4]. Therefore, it is of great value to carry out research on fault diagnosis and health monitoring of rolling bearings in ship equipment[5].

Traditional bearing fault diagnosis methods are usually based on vibration signal analysis, which combines time-domain, frequency-domain, or time-frequency-domain feature extraction and then uses a classifier to determine faults[6]. However, such methods rely heavily on manual feature design. In complex working conditions and strong noise environments, it is often difficult to extract stable and effective features, which limits the diagnostic accuracy and generalization ability[7].

Virtual Metrology uses measurable variables to estimate variables that are difficult to measure directly[8]. By establishing a mapping relationship between input variables and target variables, it can indirectly obtain key state parameters. In the field of ship equipment health management, the internal damage status of bearings is usually not directly measurable[9]. Therefore, it can be regarded as a "health variable that cannot be directly measured". A virtual measurement model can be constructed through vibration signals to estimate the health status of bearings online[10].

In recent years, deep learning methods have been widely used in mechanical fault diagnosis. CNN can automatically extract multi-level features from raw signals, while LSTM has good temporal modeling ability when processing time-series data[11]. The combination of CNN and LSTM can capture both the local impact features and long-term temporal dependencies in vibration signals, thereby improving the ability of fault identification[12]. Therefore, this paper proposes a CNN-LSTM-based virtual measurement model for ship rolling bearing faults, which realizes the end-to-end mapping from vibration signals to bearing fault states, and verifies the effectiveness of the method through multiple groups of experiments[13].

The main contributions of this paper are as follows:

(1)A CNN-LSTM virtual measurement model for ship rolling bearing fault diagnosis is proposed to realize the end-to-end mapping from vibration signals to fault states;

(2)A hybrid network structure integrating local feature extraction and temporal modeling ability is constructed to improve the accuracy of fault identification under complex working conditions;

(3)The engineering applicability of the model in the complex ship environment is verified through comparative experiments, noise robustness tests, and early fault detection experiments.

2. Modeling Strategy for Virtual Measurement

Virtual Metrology is a data-driven state estimation technique that achieves online estimation of key state parameters by establishing a mapping relationship between measurable variables and variables that are difficult to obtain directly. In complex industrial systems, some key state variables cannot be directly measured by sensors due to structural constraints or high measurement costs. Therefore, measurable process variables are usually used to construct a virtual metrology model to indirectly estimate the target variables. In ship power systems, the internal damage state of rolling bearings is difficult to measure directly with sensors, while vibration signals can sensitively reflect changes in bearing operating conditions. Therefore, the bearing fault state is taken as the target variable of virtual metrology, and vibration signals are taken as input variables to construct a data-driven model for establishing the mapping relationship between them. Let the input vibration signal be X and the bearing fault state be Y. Then the virtual metrology model can be expressed as:

$$Y=f(X) \tag{1}$$

where f(·) is the mapping function to be learned. Traditional methods usually establish this mapping through manual feature extraction and shallow classifiers. However, under complex ship operating conditions, vibration signals are often nonlinear, non-stationary, and contaminated by strong noise, making it difficult for traditional methods to obtain stable and effective feature representations. Deep learning methods can automatically learn high-level feature representations from input data through a multi-layer network structure, which is suitable for modeling complex nonlinear mappings. Therefore, deep neural networks can be used to learn features from vibration signals and construct a virtual metrology model from vibration signals to bearing fault states, so as to realize intelligent identification of fault states. Based on the above analysis, this paper adopts a deep learning model combining convolutional neural network (CNN) and long short-term memory (LSTM) network to extract features from vibration signals, model temporal dependencies, and further construct a virtual metrology model for rolling bearing fault states.Prepare Your Paper Before Styling

CNN excels at extracting local features, while LSTM is adept at modeling temporal dependencies. By combining the two, a hybrid model can be constructed, which can capture the transient impact features in vibration signals and model their long- term evolution laws, thereby improving fault diagnosis accuracy and robustness under complex operating conditions of naval ships.

3. CNN-LSTM Fault Virtual Measurement Model

3.1. Overall Structure ofthe Model

To address the spatiotemporal correlation characteristics of vibration signals in ship rolling bearings, namely the coupling of local impact mutations and long-term periodic evolution, this paper constructs a serially fused CNN-LSTM hybrid network model.The front end of the model adopts a multi-layer one-dimensional CNN module to adaptively extract local impact features and high-dimensional abstract representations from raw vibration signals.The back end is connected with an LSTM layer, which takes the feature sequence extracted by CNN as the input for temporal modeling to capture the long-term dependencies of fault features. Finally, a fully connected layer and a Softmax classifier are used to output the probability of fault states.

3.2. CNN Spatial Feature Extraction

The front-end of the hybrid network model proposed in this chapter is a CNN module, whose main task is to gradually extract highly discriminative local features from the original one-dimensional vibration signals. This section details the structural design and parameter configuration of this module. The data input to the model is the preprocessed vibration acceleration signal of the rolling bearing. The continuous time-series data are segmented into samples with a fixed length, forming a sample set $X=\{x_1, x_2, ..., x_N\}$ where each sample $x_i \in R^{1\times L}$ Lis a one-dimensional vector representing the vibration signal within a time window of length L.

The one-dimensional convolutional layer performs the key task of feature extraction. It works by applying multiple one-dimensional convolution kernels (filters) that slide over the input signal, computing feature maps through local connection and weight sharing mechanisms. Let the k-th convolution kernel be $w^k \in R^{1\times size}$, where size denotes the kernel size. Its operation on the input signal X is given by:

$$y_i^k=f\left(\Sigma_{j=1}^{size} w_j^{k\cdot} \ x_{i+j-1}+b^k\right) \tag{2}$$

where y_i^k is the output value of the k-th feature map at position i, b^k is the bias term.This paper adopts the ReLU function as the activation function, whose expression is given by:

$$f(z)= \max (0,z) \tag{3}$$

ReLU is effective in alleviating the vanishing gradient problem, accelerating model convergence, and introducing nonlinear transformations to enhance the model's representation capability.

This paper uses stacked convolutional layers. Shallow convolution kernels tend to capture simple, low-level features, while deep kernels combine these into more complex and abstract high-level features, thereby improving the model's ability to distinguish various fault patterns.

A one-dimensional max-pooling layer is added between two consecutive convolutional layers. The pooling layer mainly serves three purposes: reducing computational cost, decreasing the number of parameters, and providing translation invariance while retaining the most salient features.

3.3. LSTM Temporal Modeling

CNN performs well in extracting local features and spatial patterns from vibration signals. However, it is essentially a spatial-domain feature extractor and has limited ability to capture the dynamic temporal characteristics of long-range dependencies in time series. Vibration signals of rolling bearings are typical time-series data, whose fault features evolve along the time axis, and the signal states at adjacent time steps are strongly correlated. To further explore the temporal context information in time series, it is necessary to introduce models specialized in processing sequential data, such as the Long Short-Term Memory (LSTM) network. The core of LSTM lies in its gating mechanism and cell state. The cell state acts as a "conveyor belt" running through the entire network, transmitting information through only a few linear operations, thus enabling stable gradient flow. LSTM uses three carefully designed gates to control the information flow of the cell state.

Forget Gate: determines which information to discard from the cell state. By observing the current input xt and the previous hidden state h_{t-1} , it outputs a value between 0 and 1 for the cell state C_{t-1}. A value of 1 means "ompletely retain", while 0 means "completely forget".

$$f_t=\sigma(W_{f\cdot} \ [h_{t-1}, x_t]+b_f) \tag{4}$$

Input Gate: determines which new information is stored in the cell state. It consists of two parts~: a sigmoid layer decides which values to update, and a tanh layer generates the candidate value vector C_t.

$$i_t=\sigma(W_{i.} \ [h_{t-1}, x_t]+b_i) \tag{5}$$

$$\tilde{C}_t= \tanh (W_{C.} \ [h_{t-1}, x_t]+b_C) \tag{6}$$

Output Gate: determines the value of the next hidden state (i.e., the output) based on the cell state. The hidden state contains information from previous sequences and can be used for prediction tasks.

$$o_t=\sigma(W_{o.}\ [h_{t-1},x_t]+b_o) \tag{7}$$

$$h_t=o_t * \tanh\ (\ C_t) \tag{8}$$

This gating mechanism enables LSTM to selectively memorize or forget information, thus effectively modeling complex dynamic variations in long time series.

The application of LSTM to rolling bearing fault diagnosis has three main advantages: strong temporal modeling capability, stability with respect to sequence length, and the ability to remember long-term historical information. LSTM can well capture the periodicity, attenuation trends, and dynamic response characteristics of fault impacts in vibration signals, which is crucial for accurately classifying fault types. Moreover, its gating mechanism allows flexible processing of variable-length time-series signals, resulting in stronger adaptability compared with CNN, which requires fixed-size inputs.

In addition, the unique cell state structure of LSTM supports selective retention of long-term historical information and preserves early events that critically influence current state judgment, enabling continuous tracking of the fault evolution process. This feature allows it not only to identify existing faults but also to capture early fault precursor features, enabling earlier and more accurate fault prediction, and providing strong technical support for the health state assessment of rolling bearings.

4. Experiments and Result Analysis

To comprehensively verify the effectiveness of the model in shipboard applications, this paper designs three sets of experiments for simulation and comparative analysis.

4.1. Dataset and Experimental Setup

The experimental data are obtained from a rotating machinery bearing test platform, which simulates typical shipborne rotating machinery. Vibration signals under normal and various fault conditions are collected using vibration acceleration sensors. The sampling frequency of the vibration signal is 12 kHz, with 2048 data points per sample. The dataset contains 10 groups of samples, including 1 group of abnormal samples. To simulate the noise in the complex environment of a ship cabin, Gaussian white noise with different signal-to-noise ratios is added to part of the test set.

The dataset is divided into training, validation, and test sets with a ratio of 6:2:2. The model parameters are set as follows: three CNN convolutional layers with 16, 32, and 64 kernels respectively; the number of hidden units in the LSTM layer is 64. During model training, the batch size is set to 64 and the learning rate to 0.001.

To comprehensively validate the overall performance of the proposed CNN-LSTM hybrid network model in rolling bearing fault diagnosis, three sets of experiments are designed in this chapter for simulation analysis and in-depth discussion. The experiments are conducted progressively from three aspects: basic diagnostic performance, anti-noise capability, and early fault warning, forming a complete performance evaluation system, which provides reliable evidence for the effectiveness and engineering practical value of the model.

4.2. Experiment 1: Baseline Model Comparison Experiment

This experiment conducts a systematic comparative study with baseline models to verify the overall performance of the proposed CNN-LSTM hybrid model in rolling bearing fault diagnosis. Representative traditional machine learning methods and deep learning models are used for comparison, including the support vector machine model based on manual features, the single convolutional neural network model, and the single long short-term memory network model.

To ensure experimental fairness, all comparison models are trained and their hyperparameters optimized using the same training and validation sets, and their performance is finally evaluated on a unified test set. Model performance is quantitatively assessed using four key metrics: accuracy, precision, recall, and F1-score.

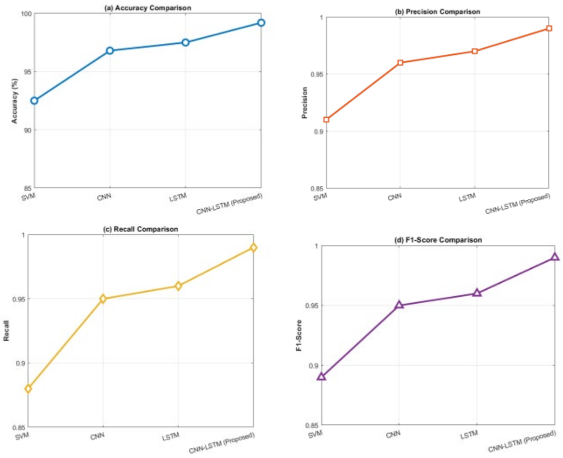

Figure 1: Early Fault Detection Test series ofline charts

Figure 1 clearly shows the performance comparison among different models. The overall analysis indicates that the proposed CNN-LSTM hybrid model outperforms the baseline models across all evaluation metrics. Its diagnostic accuracy reaches 92. 1%, while precision, recall, and F1-score all exceed 98.0%. The CNN module contributes its advantage in effectively extracting local impact features from vibration signals, and the LSTM module successfully captures the temporal evolution and long-term contextual dependencies of fault features. Meanwhile, the end-to-end feature learning scheme overcomes the subjectivity and limitations of manual feature extraction in traditional methods, resulting in superior generalization performance and diagnostic accuracy. To analyze the diagnostic performance of different models more clearly, the experimental results are summarized in the following Table 1.

Table 1: Performance comparison of differentfault diagnosis models

Model	Accuracy	Precision	Recall	F1-score
SVM	83.1%	91.4%	90.8%	91.1%
CNN	86.5%	96.1%	95.8%	96.0%
LSTM	86.7%	95.3%	95.1%	95.2%
CNN-LSTM	92.1%	98.0%	98.1%	98.4%

As can be seen from Table 1, the traditional machine learning method SVM achieves an identification accuracy of 83. 1% in the bearing fault diagnosis task, while the deep learning models CNN and LSTM reach 86.5% and 86.7% respectively. This indicates that deep learning methods have certain advantages in extracting features from complex vibration signals. The CNN-LSTM model proposed in this paper combines the local feature extraction ability of convolutional neural networks with the temporal modeling ability of long short-term memory networks, and performs significantly better than other comparison models, with an identification accuracy of 92. 1%. This shows that the proposed method can more effectively extract fault features from bearing vibration signals, thereby improving fault identification performance.

4.3. Experiment 2: Noise Robustness Test

This experiment aims to verify the reliability of the proposed CNN-LSTM hybrid model in industrial environments with strong noise interference, and systematically evaluates the performance of each model under different signal-to-noise ratio conditions. Gaussian white noise of varying intensities is added to the clean test set signals to construct noisy test sets with signal-to-noise ratios of 20, 15, 10, 5, 0, and _5 dB respectively, simulating noise environments ranging from mild to extreme.

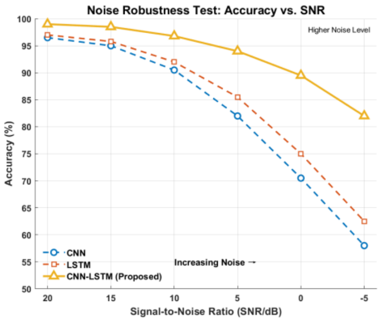

Figure 2: Noise Robustness Test: Accuracy vs. SNR.

The trained CNN-LSTM model was tested under various signal-to-noise ratio conditions, and the accuracy was recorded. The results show that as noise increases (SNR decreases), the performance of all models degrades, which is illustrated in Figure 2. However, the CNN-LSTM model maintains the highest accuracy under all SNR conditions, and its performance degrades the slowest in low-SNR (high-noise) environments, demonstrating strong anti-interference ability and robustness. This is attributed to the combined effect of the local feature extraction by the CNN module and the insensitivity of the LSTM module to temporal noise, which enhances the practical value of the model in harsh industrial environments.

4.4. Experiment 3: Early Fault Detection Test

To verify the detection capability of the proposed CNN-LSTM hybrid model for incipient weak faults, this experiment conducts a graded evaluation of model performance according to fault severity. Abnormal data in the test set are divided into three levels based on the fault development process: Level 1 represents slight faults with weak abnormal characteristics; Level 2 represents moderate faults with relatively obvious characteristics; Level 3 represents severe faults with prominent characteristics. Subsequently, the recall rate of abnormal data at each level is calculated for different models to evaluate the model's ability to detect abnormal samples.

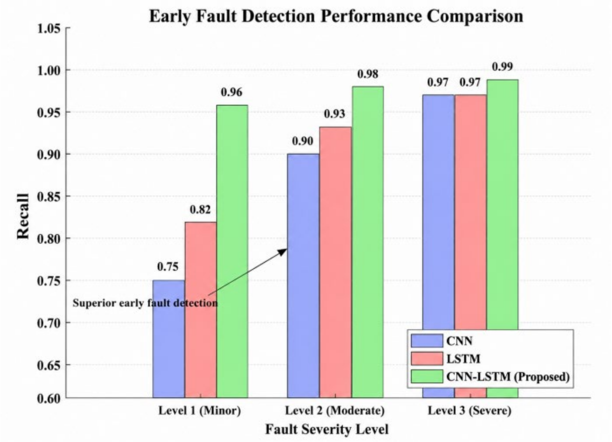

Figure 3: Early Fault Detection Performance Comparison

As depicted in Figure 3, experimental results show that all models achieve relatively high recall rates for Level 3 severe faults. However, in the detection of Level 1 incipient weak faults, the CNN-LSTM model achieves a much higher recall rate than the single CNN or LSTM model. This indicates that the CNN module can effectively enhance the extraction of weak impact features, while the LSTM module can capture the long-term evolution and weak precursors of faults. Their synergy significantly improves the sensitivity to early faults, providing reliable technical support for predictive maintenance. To verify the effectiveness and superiority of the proposed CNN-LSTM virtual measurement model in rolling bearing fault identification, the Convolutional Neural Network (CNN) and Long Short-Term Memory network (LSTM) are selected as comparison models. Fault diagnosis experiments are carried out under the same dataset and experimental conditions. The diagnostic accuracy of different models is compared to comprehensively evaluate the performance of the proposed method. The experimental data are presented in Table 2.

Table 2. Comparison offault diagnosis performance ofdifferent models

Model	Overall Diagnostic Accuracy/%
CNN	86.5
LSTM	86.7
CNN-LSTM	92. 1

5. Conclusion

This paper proposes a virtual measurement method for shipborne rolling bearing faults based on CNN-LSTM, which maps vibration signals to bearing fault states in an end-to-end manner. A hybrid deep learning model is constructed by combining the local feature extraction capability of CNN with the temporal modeling capability of LSTM, thereby improving the accuracy of fault identification under complex operating conditions. Experimental results show that the proposed model outperforms traditional machine learning methods and single deep learning models in diagnostic accuracy, anti-noise performance, and early fault recognition, with an overall diagnostic accuracy of 92. 1%. In addition, the method exhibits strong robustness in heavy noise environments and can effectively detect weak early faults. Research indicates that this method enables high-precision virtual measurement of the health status of key components in ship power systems, and has significant engineering application value for intelligent operation and maintenance as well as condition monitoring of shipboard equipment.

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