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Design of Fault Diagnosis and Fault Prediction System for Stacker Traveling Mechanism Based on Digital Twin

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Abstract. This paper addresses the typical fault diagnosis and prediction problems of stacker cranes in the intelligent manufacturing process. Firstly, a digital twin of the target object is constructed, achieving the modeling of physical space modules, digital space modules, twin database modules, application system modules, and connection modules. Through data mapping, the geometric model of the walking wheel mechanism's digital twin is made to correspond to the physical entity of the walking wheel mechanism. Data collected from the physical entity is used to drive the digital twin model in real time, enabling the identification and prediction results of bearing faults to be reflected in the digital twin. Then, for the typical fault diagnosis and prediction process of the walking mechanism, a wavelet transform method is provided to convert vibration signals into time-frequency image features. The time-frequency feature map is used as the input of the 2D-CNN network to ultimately achieve fault diagnosis. At the same time, the convolutional layer, pooling layer, fully connected layer, and classification layer of the recognition model are optimized. Finally, a simulation experiment is set up. In the experiment, the bearing fault datasets from Case Western Reserve University and Xi'an Jiaotong University are used as the training and testing datasets. Through comparative experiments, the method proposed in this paper can improve the recognition accuracy and efficiency in bearing fault diagnosis and prediction.

Keywords: stacker crane, convolutional network, wavelet transform, digital twin

1 Introduction

As the most crucial core handling equipment in automated high-rise warehouses, stacker cranes have solved the problem of delivering and retrieving goods from high shelves. The number and frequency of their use have been increasing with the growth of intelligent manufacturing businesses. The efficiency of parts flow and logistics handling in the intelligent manufacturing process has been significantly improved with the introduction of stacker cranes, while labor costs have been effectively reduced. The efficient operation of the entire intelligent manufacturing process and logistics system is thus guaranteed [1].

The general structure of a stacker crane is divided into two parts: the ground running track and the top cargo handling tool. From the perspective of the structural movement coordinate, there are three movement directions: X, Y, and Z, which correspond to the horizontal running mechanism, the fork extension mechanism, and the vertical lifting mechanism, respectively. Any malfunction in any part will interfere with the stacker crane's storage and retrieval of goods, causing the entire logistics system to come to a standstill and even resulting in significant economic losses [2]. The common faults of stacker cranes are summarized [3] as follows:

1) Walking faults caused by the wear of the walking wheels, such as uneven wear on the walking wheels, wear on the walking wheel shaft and bearings, and periodic abnormal noise during the walking process.

2) Installation loosening or structural damage faults, such as deformation and damage to the walking track,

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and damage to the force-bearing structure of the traction mechanism, which cause the stacker crane to fail to operate normally.

3) Unstable operation faults caused by lack of lubrication, such as lack of lubricating oil on the walking mechanism shaft, lack of lubricating oil on the guide wheel shaft, and excessive gap between the guide rail and the guide wheel.

Summarizing the above-mentioned fault characteristics of the stacker crane, the trend faults of the stacker crane mainly occur at the contact points of various components, with the walking wheel faults being the most prominent. As a key component of the horizontal running structure, the walking wheel mechanism not only bears the basic loads such as the self-weight of the stacker crane, the lifting load of the goods, and the traction force of the motor, but also is subjected to various impact loads during the walking process. Its working conditions are complex and changeable, featuring low-speed heavy loads, harsh working environments, and even alternating stress scenarios [4]. During the operation of the stacker crane, once serious faults occur in the walking wheel mechanism, such as the failure of rolling bearings, damage to the walking wheels, bending of the rotating shaft, and torsional deformation, these faults will impede the normal operation of the horizontal running mechanism, thereby causing the entire production line to stop, resulting in direct economic losses. Therefore, timely preventive and restorative maintenance of the stacker crane is the only way to avoid losses and faults. For the fault diagnosis and prediction of the traveling mechanism of stacker cranes, the work done in this paper is as follows:

1) A method for constructing the digital twin model of the stacker crane and the communication model between the digital twin model and the real equipment is provided;

2) A vibration frequency acquisition method for typical bearing faults of the traveling mechanism of stacker cranes and a wavelet transform scheme for converting frequency domain features into time-frequency images are provided;

3) An improved deep learning method is used to achieve the identification of bearing faults and the prediction of early faults;

4) A simulation environment is constructed, a bearing vibration data set is established, and the training and testing of the model are completed.

2 Related Work

The research content of this article is to construct a structural model of the stacker crane using digital twin technology, and then use intelligent neural networks to autonomously judge and predict typical faults of the stacker crane's traveling mechanism, improving the accuracy of fault diagnosis and prediction. Then, the overall framework and technical route of the fault diagnosis system are proposed. The current research status related to digital twin and fault diagnosis is summarized and analyzed, and it is summarized into three stages of fault diagnosis for the traveling mechanism:

The first stage is the expert experience-led phase, which requires the collection of a large amount of historical fault data to form an expert database qualitatively. Then, faults are determined manually. This stage demands a high theoretical level from technicians. Xinjian Zhou from Xi'an University of Science and Technology conducted a study on the walking mechanism of coal mining machines using the Fault Tree Analysis method. Firstly, he identified the failure factors of the walking mechanism and established a Fault Tree model for it. Then, he carried out a qualitative analysis of the Fault Tree model using the Minimal Cut Set method [5]. This professional-oriented stage is crucial since it provides the basis for primary fault diagnosis but is marred by human experience and manual exploration. This stage is typically used in industries where there are no correct automated models at the moment but takes a lot of labor and is susceptible to human errors. Ting Lv, in response to the complexity and uncertainty of stacker crane equipment during operation, designed a hybrid diagnostic expert system based on fault tree and Bayesian network, effectively addressing the problems of single reasoning mode and difficult knowledge acquisition in traditional diagnostic expert systems by leveraging the advantages of both fault tree analysis and Bayesian network algorithms [6].

The second stage is the data-driven stage. In this stage, there is no need to build an accurate mathematical model of equipment failure. Instead, sensors and other devices collect information and process and analyze it to predict faults. The accuracy rate has been effectively improved compared to the first stage, but it still requires some human assistance. Muralidharan extracted the vibration signals of bearing faults from the experimental device and then used the continuous wavelet transform (CWT) to calculate for different families and different levels to form a fault feature set. Finally, decision tree and fuzzy logic methods were used for diagnosis [7].

The use of CWT for feature extraction is a significant improvement in this stage as it allows for more accurate and detailed fault detection through the decomposition of complex signals into comprehensible features. This approach is a shift from qualitative analysis to more data-driven diagnostics. Zheng Wang introduced the analysis process of a 220 kV transformer internal partial discharge fault. Through comprehensive diagnostic analysis of the transformer's chromatographic analysis, on-line ultrasonic partial discharge detection, off-line diagnostic tests, and induced withstand voltage partial discharge tests, it was determined that there was an arc discharge phenomenon inside the transformer [8]. Tao Zhang proposed a method for collecting fault data of hoists and conducting big data analysis on the data, and gave a fuzzy comprehensive evaluation method for the health status of hoists. The method can effectively predict the faults of hoists [9].

The third stage is the multi-method fusion intelligent prediction stage. The development of technologies such as deep learning, neural networks, and digital twins has further improved the accuracy of fault prediction algorithms, enabling computers to directly make judgments on equipment status. Weixin Yang proposed a digital twin-driven three-dimensional visualization real-time monitoring and fault early warning method for wind turbine units. A framework for a three-dimensional visualization real-time monitoring and fault early warning system for wind turbine units based on digital twins was constructed. The framework is based on a cloud-edge collaborative data collection and governance method for wind turbine units. By using WebGL and 3D model lightweighting technology, a Web-based three-dimensional visualization monitoring of wind turbine units was achieved [10]. Jingyan Xia from South China University of Technology proposed a small sample fault diagnosis method for mechanical equipment driven by the fusion of twin data and feature enhancement. A virtual model of the mechanical equipment was constructed, and the model was optimized and corrected by combining the operation mechanism knowledge of the equipment and the measured data of the health status to obtain a high-fidelity model. Then, high-quality twin fault data was obtained based on this model, and the feature enhancement of the equipment twin fault data was carried out using a generative adversarial network. The enhanced data was used for the training of the convolutional neural network model, thereby achieving intelligent fault diagnosis of the equipment [11]. Feature augmentation using generative adversarial networks is the key innovation during this period because it allows for the creation of high-quality fault data from limited samples, which can improve training for machine learning models and consequently diagnostic accuracy.

3 Digital Twin Architecture and Modeling of Walking Mechanism

This article divides the overall architecture of digital twins into five layers, namely the physical space module, the digital space module, the twin database module, the application system module, and the connection module [12]. The overall framework of the twin model is shown in Fig. 1.

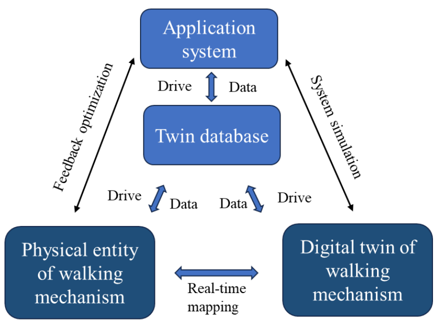

Fig. 1. The structure of the digital twin model of the stacker crane traveling mechanism

1) The physical space model stores the physical entity model of the walking mechanism of the stacker crane in the real environment. During the modeling process, the structural composition, operational status, and functional use of the mechanism are first clarified. Based on this, a five-dimensional digital twin model of the walking wheel mechanism is constructed. Then, the model is regarded as the data source of various models of the walking mechanism digital twin to complete data mapping.

2) The digital space module stores the digital twin of the walking mechanism. The corresponding data information of the walking wheel mechanism in the physical space is obtained through four parts: geometric model, rule model, behavior model, and physical model, respectively, to capture its essential characteristics from different dimensions. On this basis, the digital twin model of the stacker crane walking mechanism is integrated and fused.

3) The twin data module, acting as a communication bridge between the physical space and the digital space, provides the full-process data-driven support for the five-dimensional model of the entire walking mechanism. Driven by the twin data of the walking mechanism as the power source in real-time, a high-precision and complete dynamic model of the digital twin is constructed, enabling real-time online data simulation and display for the identification of typical bearing faults and early fault prediction in the walking mechanism.

4) The application system module encloses various data, algorithms, results, and solutions during the operation of the digital twin model of the stacker crane walking mechanism. The establishment of the application system effectively avoids the drawback of overly complex internal systems in digital twins.

5) The connection process among the various parts in the five-dimensional model of the walking mechanism is as follows: Firstly, the interaction between the physical entity of the walking mechanism as the data source and each part is analyzed. The real-time data from the physical space is transmitted to the digital space, twin database, and application system through sensors, acquisition cards, and other devices. After the data is well stored, it is utilized for the update and iteration of the model and system. The above-mentioned three modules, after analyzing and processing the data, obtain certain identification and prediction results. Typical fault diagnosis and early fault prediction can regulate and optimize the operation of the physical entity. This section mainly accomplishes the construction of the rule model and data model of the walking mechanism. The overall structure of the digital twin model is shown in Fig. 2.

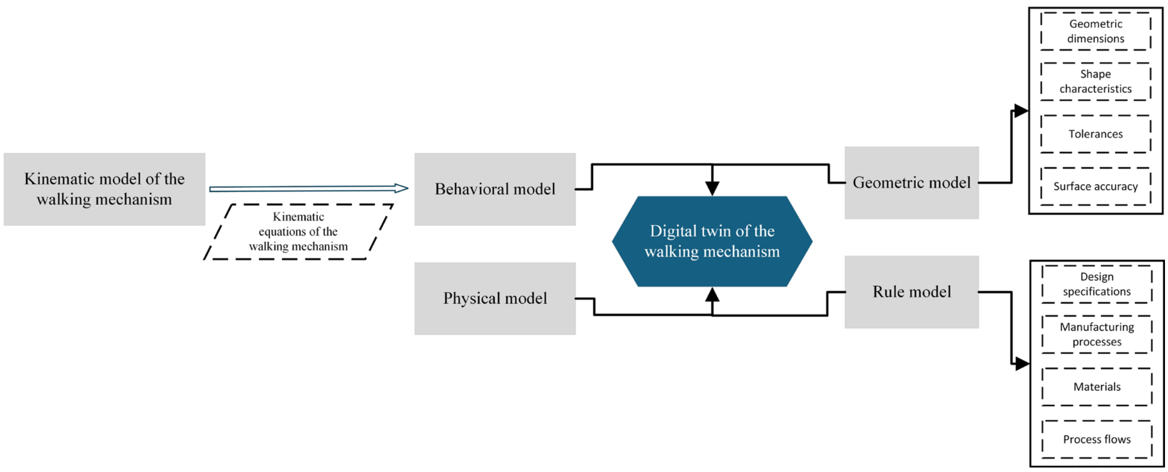

Fig. 2. Overall framework structure of the digital twin model of the walking mechanism

3.1 Establishment of Digital Twin Rule Model for Walking Mechanism

The geometric model of the digital twin of the walking mechanism corresponds to the physical entity of the walking wheel mechanism. Data collected from the physical entity is used to drive the digital twin model in real time, thereby enabling an intuitive display of the physical entity. Meanwhile, the target data of the physical entity can be displayed on the digital twin entity [13]. The structure of the digital model construction is shown in Fig. 3.

In the process of 3D modeling, SolidWorks software was used for 3D modeling in this paper. After design, the model of the walking mechanism of the stacker crane finally constructed in this paper is shown in Fig. 4.

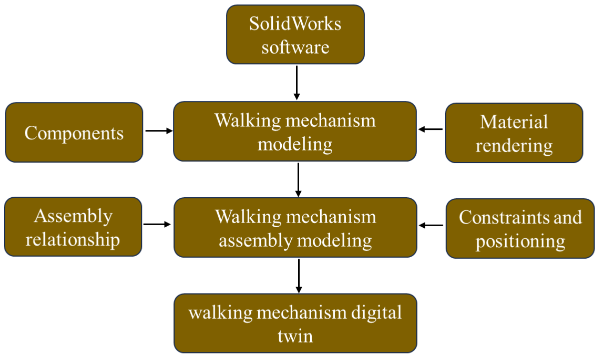

Fig. 3. Schematic diagram of the geometric model construction process of the digital twin of the walking mechanism

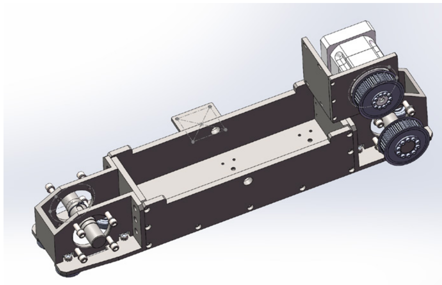

Fig. 4. Schematic diagram of the 3d model construction results

The design and construction of the rule model for the walking mechanism should follow the normal working scenarios. During the modeling process, the force conditions of the walking mechanism are mainly analyzed for force analysis, and the model is established by referring to the crane design manual, mechanical design manual, actual on-site working conditions, and expert experience, etc. The rule model of the walking mechanism digital twin in this paper can be divided into three sub-models: the working level model of mechanical structural components, the load classification and calculation model of the walking mechanism, and the load combination model [14]. The parameters involved in the construction of the rule model are shown in Table 1.

Table 1. All parameter lists in the rule model

Parameter name	Parameter description
L_{use}	The usage status of mechanical parts of the walking mechanism composed of the total profit cycle times
L_{state}	Stress state of components
L_{work}	Working status of the walking mechanism
k_{stress}	Stress spectrum coefficient
n	Stress cycle and working round-trip times of the walking mechanism
$\sigma_{\max}$	Total stress of the walking mechanism
σ_i	Stress of different component parts of the mechanism
λ	Indicates the power exponent
F_{total}	Indicates the total load of the walking mechanism
$G_{stacker}$	Self-weight of the stacker crane
F_{load}	Load of the stacker crane
F_{ac}	Load caused by the speed change during the acceleration and deceleration process of the walking mechanism
β_1	Impact coefficient
β_2	Dynamic load coefficient
β_3	Acceleration (deceleration) dynamic load coefficient

3.2 Model of Working Level for Mechanical Structural Components

The working condition of the mechanical structural components of the walking mechanism is influenced by two parameters: the total number of stress cycles and the stress situation. The working condition is expressed as:

$$L_{work} = \left[L_{use}, L_{state}\right] \tag{1}$$

When the walking mechanism is in operation, the number of its back-and-forth movements is generally no less than ten thousand times. Therefore, it can be stipulated that the number of cyclic stresses the walking mechanism is subjected to throughout its operation is no less than one hundred thousand times. Thus, the usage status of the walking mechanism is further classified based on the number of back-and-forth movements, and the classification results are presented as follows:

$$L_{use} = \begin{cases} L_{use.1} & 1\times10^6 \le n \le 3\times10^6 \\ L_{use.2} & 3\times10^6 \le n \le 6\times10^6 \\ L_{use.3} & 6\times10^6 \le n \le 9\times10^6 \\ L_{use.4} & 9\times10^6 \le n \end{cases} \tag{2}$$

The stress spectrum coefficient is expressed as:

$$0.6 \le k_{stress} = \sum\left[\frac{n_i}{n}\left(\frac{\sigma_i}{\sigma_{\max}}\right)^{1-\lambda}\right] \le 1 \tag{3}$$

3.3 Classification and Calculation of Load for Walking Mechanism

The load causes stress load in the stacker crane through temperature, displacement and force, etc. The stacker crane is subjected to various loads such as regular load, accidental load and acceleration load during actual operation. In order to simplify the regular model of the traveling mechanism, the model established in this paper only considers the regular load. The regular load is mainly divided into self-weight load, load load and load caused by variable speed operation. The mathematical expression of the load is as follows:

$$F_{total} = G_{\text{stacker}} + F_{load} + F_{ac} \tag{4}$$

Self-weight load refers to the load generated by the structure of the stacker itself. When the items are lifted off the ground or lowered to the ground, the stacker will vibrate due to the self-weight load and generate a pulse response. Vibration generates impact, so the impact coefficient is expressed as:

$$\beta_1 = 1 \pm \alpha, \alpha \in \left[0, 0.1\right] \tag{5}$$

Load capacity refers to the total weight of the load lifted by the stacker crane each time during its actual operation, including the weight of the goods and the lifting gear. When the items are lifted off the ground, the load capacity will increase due to the inertial force. To consider the load capacity, the dynamic load coefficient β_2 is introduced, which is related to the lifting speed of the stacker crane and the working stress state. The load caused by variable speed operation refers to the load caused by the acceleration or deceleration of the stacker crane's driving mechanism. To reflect the elastic effect of the actual variable speed load, the dynamic load coefficient β_3 for the acceleration (deceleration) of the mechanism drive is introduced during calculation, and β_3 is related to the change in the driving force of the speed.

3.4 Construction of Load Combination Model

The probability of all the loads that the stacker crane and its structural components bear occurring simultaneously is very low. Therefore, when establishing the load combination model, a comprehensive consideration should be given based on the working characteristics and different working conditions of the stacker crane. The principle of load combination is to combine the possible loads according to the most unfavorable working condition of the traveling mechanism. The limit state method is adopted in the calculation. The typical combination and calculation process is shown in Fig. 5.

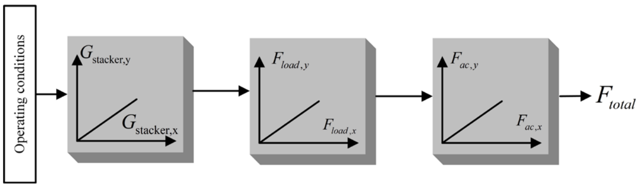

Fig. 5. Diagram of load combinations and calculation process

3.5 Digital Twin Data Mapping

The operation scenarios, load scenarios and fault prediction models of the walking mechanism are virtually reproduced in real time or quasi real time. After the data is transmitted and parsed, it will be called in the process of formulating logical rules to drive the behavior simulation of the main components in the walking mechanism. The virtual-real mapping at the equipment level aims to reproduce the behavior and status of the walking mechanism in the virtual space through a data-driven approach; the mapping at the information level is dedicated to visualizing the production line information in the virtual space. The implementation process of data mapping can be divided into two stages: the initial state matching stage and the stable dynamic driving stage.

1) Initial state matching stage: When the digital twin system of the walking mechanism starts, multiple models in the digital twin will quickly match the operating state of the physical walking mechanism and remain consistent. This stage completes the following initialization operations through the matching module: Firstly, the string data composed of the signal field names of the walking mechanism is registered to facilitate the subsequent call of signal data; Secondly, the operating speed of the walking mechanism model is set based on the measured value of the physical entity's operating speed or the data provided by the upper-level information system; Finally, the animation speed that constitutes the equipment behavior model is set to zero to ensure that the system can respond quickly to the current instructions when it starts. The essence of the initial state matching is to pre-load the basic tool classes required in the virtual-real mapping process, reset the operating equipment, and quickly match the real-time data, thereby ensuring that the operating components of the walking mechanism (such as bearing status, etc.) are consistent with the state of the physical entity when the digital twin system starts.

2) Stable dynamic drive stage, After the initialization state matching stage is completed, the digital twin system will enter a long-term stable dynamic driving stage. During this stage, as the physical walking mechanism is in a continuous reciprocating operation state, all its driving data show dynamic change characteristics. The digital twin system driven by real-time data can comprehensively reflect the behavioral changes, state transitions, and information updates of the physical walking mechanism.

3.6 Establishment of Digital Twin Data Model for Walking Mechanism

The data model consists of three parts: the twin data of the walking mechanism, data connection, and twin simulation. The twin data of the walking mechanism is the data for communication between the physical model and the twin model of the stacker crane, which records the operation status of the stacker crane and dynamically monitors its working state. Data connection refers to the seamless connection between the physical model and the twin model of the walking mechanism, the signal connection between the digital twin platform Visual Components and the Programmable Logic Controller (PLC), as well as the connection among various components of the stacker crane's three-dimensional warehouse. The twin simulation of the stacker crane mainly includes the modeling and simulation of the stacker crane model in SolidWorks software. Meanwhile, Siemens TIAportal software can be used to view the running position and speed of the walking mechanism in real time [15].

The signal connection between the digital twin platform Visual Components and the PLC is the process of connecting the input and output signals of the stacker crane node created in the digital twin platform Visual Components to the variables in the PLC ladder diagram one by one through the OPC UA server at 192.168.0.2. The digital twin platform Visual Components is connected to the PLC. The fault identification algorithm runs in the background. The operation status data of the traveling mechanism includes the bearing vibration frequency collected by the vibration sensor, which is processed through time-frequency transformation.

SolidWorks software modeling and simulation is the process of assembling the individual mechanisms of the stacker crane after their design is completed to verify the feasibility of the stacker crane assembly and the rationality of its motion. The virtual simulation of the digital twin platform Visual Components is the process of importing the 3D model of the stacker crane into the digital twin platform Visual Components, setting the node features and motion parameters, and making it move virtually. The virtual debugging in the PLC is the process of writing the ladder diagram for the motion process of the stacker crane in the Siemens TIAportal software and downloading it to the virtual simulator for compilation and simulation. The OPC UA communication simulation between the digital twin platform Visual Components and the PLC using the PLC-SIM Advance software is the process of setting the server address to 192.168.0.2 in the PLC-SIM Advance software, allowing both the digital twin platform Visual Components and the PLC to log in to the server simultaneously, and connecting the signals in the digital twin platform Visual Components to the variables in the PLC one by one [16].

4 Fault Diagnosis and Prediction of Walking Mechanism

From the analysis of the first section, it can be known that due to the frequent reciprocating operation of the stacker crane, the faults mainly concentrate on the traveling mechanism. The common faults of the traveling mechanism are bearing faults. As an important load-bearing component of the traveling wheel mechanism, the bearing is subjected to self-weight load, lifting load, impact load, etc. Due to its long-term operation in an extreme working environment, it may cause a certain degree of damage to itself. After a period of expansion and accumulation, it will form a relatively obvious fault. Typical bearing faults are shown in Table 2.

Table 2. Common faults of rolling bearings in walking mechanism

Bearing components	Common faults
Inner ring of bearing	Corrosion, wear, fracture, indentation, fatigue spalling
Outer ring of bearing	Corrosion, wear, fracture, indentation, fatigue spalling
Bearing rolling elements	Corrosion, wear and fatigue of pineapples
Bearing cage	Corrosion, wear and tear

Bearing fault diagnosis is based on the feature characterization of bearing vibration signals. How to identify the vibration signals of bearing faults is the key to fault diagnosis. Due to the low computational depth of the one-dimensional convolutional neural network (1D-CNN) model, its ability to extract complex features is limited, resulting in the prediction effect of the classification model not reaching the ideal level. Therefore, to improve the prediction accuracy of the model, this paper applies the two-dimensional convolutional neural network (2D-CNN) model to the prediction of walking mechanism bearing faults, in order to effectively assess the operational risks of stacker cranes. Compared with the unidirectional movement of the 1D-CNN convolution kernel, the 2D-CNN convolution kernel adopts a bidirectional movement method, which can more effectively extract the time-frequency features of vibration signals, thereby improving the accuracy of fault diagnosis. Therefore, in this paper, the mutual information method is adopted to align the sound and vibration signals, and then the time-domain signals of the bearings are converted into time-frequency images. The 2D-CNN network is used to extract the fault features in the two-dimensional time-frequency images respectively [17], forming a fault feature set, and completing the training and recognition of the bearing fault model.

4.1 Signal Processing

The signal alignment strategy is as follows. Taking two unaligned sound and vibration signals A and B as an example. Set a sampling frame of length t on the two signals, and calculate the correlation of the sound and vibration time-domain signals in the sampling frame. The time-domain correlation calculation formula is:

$$Cor(A,B)=\frac{Cov(A,B)}{\sqrt{D(A)\cdot D(B)}}=\frac{E(AB)-E(A)E(B)}{\sqrt{E(A^2)-E^2(X)}\sqrt{E(B^2)-E^2(B)}} \quad (5)$$

The principle diagram of the alignment process of sound and vibration signals is shown in Fig. 6.

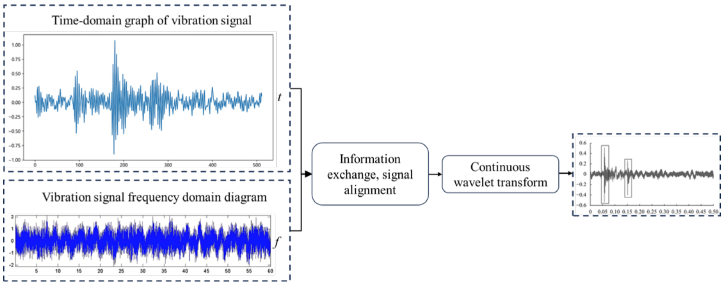

Fig. 6. Schematic diagram of the principle of alignment of sound and vibration signals

The aligned time-domain signal is converted into a two-dimensional time-frequency signal. In this paper, the Continuous wavelet transform method is used to achieve the signal conversion [18]. Continuous wavelet transform (CWT) is a technique that can conduct local and detailed analysis of signals in both time and frequency domains. Through scale and translation operations, CWT can achieve multi-scale refined analysis of signals and effectively capture local features within the signals, especially suitable for the processing of transient and non-stationary signals. Specifically, by sliding and scaling the wavelet in the time domain and computing the inner product with the signal, CWT can generate coefficients that reflect the similarity between the signal and the wavelet at different scales and frequencies. These coefficients can be used for the fusion analysis of different types of signals. Based on the research of vibration signals from the rolling bearings of walking mechanisms, combined with their signal characteristics, this paper starts from the collection and construction of vibration simulation signals of rolling bearings and explores the best signal processing method for this scenario based on the performance of time-frequency images.

Let the time-domain signal of the walking mechanism be represented as $S(t)$, then the Fourier transform of $S(t)$ is expressed as:

$$\begin{cases} F(\omega)=\int_{-\infty}^{+\infty} S(t)e^{-i\omega t}dt \\ \int_R \frac{|F(\omega)|^2}{|\omega|}d\omega<\infty \end{cases} \quad (6)$$

In the formula, $F(\omega)$ represents the Fourier transform, and R represents the spatial dimension of the sound frequency. Integrating the Fourier function in the time domain in the wavelet transform results in 0, indicating that the DC component of the wavelet function is 0. Due to the energy signal characteristics of $F(\omega)$, it can be inferred that the feature of the wavelet function is to oscillate near the origin and approach the horizontal coordinate axis as it moves away from the origin. By scaling and translating the wavelet function, the wavelet basis function is obtained:

$$F_{\kappa,\mu}(t) = \frac{1}{\sqrt{|\kappa|}} F\left(\frac{t-\mu}{\kappa}\right) \tag{7}$$

Let $F_{\kappa,\mu}$ represent the wavelet function family, κ the scale factor, and μ the time factor. Introduce a normalization constant to ensure that the total energy of the wavelet basis functions remains unchanged under different scale factors.

$$\left\|F_{\kappa,\mu}(t)\right\|^2 = \int_{-\infty}^{+\infty} \left|\frac{1}{\sqrt{|\kappa|}} F\left(\frac{t-\mu}{\kappa}\right)\right|^2 dt \tag{8}$$

The Fourier transform representation of the wavelet mother function is:

$$F_{\kappa,\mu}(\omega) = \frac{1}{\sqrt{|\kappa|}} \int_{-\infty}^{+\infty} F\left(\frac{t-\mu}{\kappa}\right) e^{-i\omega t} dt \tag{9}$$

For the time-domain and frequency-domain ranges of the wavelet transform at a single scale, the time window and frequency window of the continuous wavelet can be derived. The time-frequency window of the continuous wavelet function is a rectangle on the time-frequency plane that varies with the scale factor κ. When κ gradually increases, the time window of the wavelet widens, the frequency window narrows, and the main frequency decreases to match the low-frequency components; when κ gradually decreases, the time window of the wavelet narrows, the frequency window widens, and the main frequency increases to match the high-frequency components. This variation of the wavelet basis function with the scale factor κ endows the wavelet with the ability to focus on the frequency spectrum. The signal is reconstructed using the double integral of the wavelet coefficients.

4.2 Signal Feature Extraction

This paper employs multiple 2D-CNNs to extract fault features from sound and vibration signals, rather than for fault classification. The feature extraction process of time-frequency images mainly involves convolutional layers, pooling layers, fully connected layers, and classification layers (Softmax), as well as some optimization steps such as random dropout. The convolution process is shown in Fig. 7.

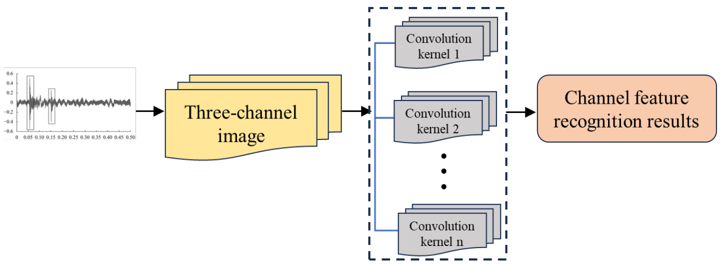

Fig. 7. Diagram of network convolutional structure recognition

The activation function uses the Leaky Rectified Linear Unit (Softmax), and the representation of the activation function is shown in Fig. 8.

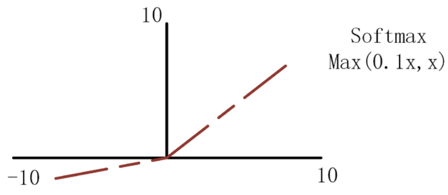

Fig. 8. Representation methods of activation functions

The main purpose of pooling is to compress the image through downsampling without affecting the quality of the input image, which helps to reduce computational complexity, enhance feature representation, and can also help reduce the risk of overfitting. The pooling process is shown in Fig. 9:

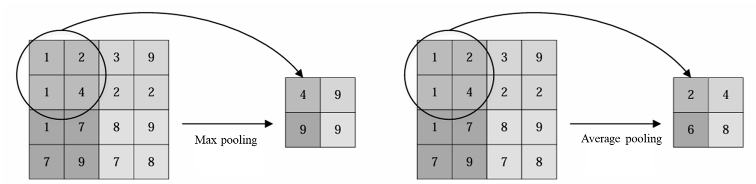

Fig. 9. Schematic diagram of the working principle of the pooling layer

The fully connected layer flattens the output of the pooling layer into a one-dimensional vector and then connects it to the output layer. This connection method is the same as that of traditional neural networks. After the fully connected layer, the ReLU function is used as the activation function, while the Softmax function is used as the activation function of the output layer. The expressions are as follows:

$$Soft\max\left(y_i\right)=\frac{e^{y_i}}{\sum_{i=1}^{n}e^{y_i}}\in\left(0,1\right) \tag{10}$$

y_i represents the i-th output of the last fully connected layer. During the model training process, some neurons are temporarily ignored, which is equivalent to each batch of the training process handling different models, similar to integrating multiple models and taking the average of their results, effectively offsetting the overfitting of a single neural network. At the same time, by deleting some neuron connections, Dropout can also accelerate the training speed of the model. This method improves the generalization ability of deep learning models by introducing randomness and the idea of integration, making them more suitable for small sample data and large-scale parameter scenarios. The working principle of this mechanism is shown in Fig. 10.

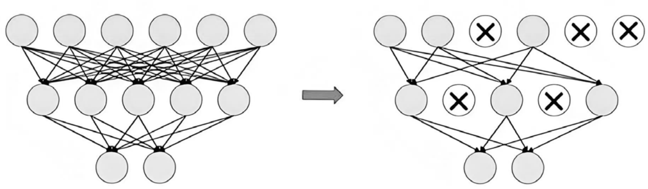

Fig. 10. Schematic diagram of the dropout process

The training of 2D-CNN mainly consists of two key steps: forward propagation and backward propagation. In forward propagation, data is passed through the network layers layer by layer, and after operations such as convolution, pooling, and fully connected layers, the final output result is obtained. In backward propagation, the gradients of the network parameters are calculated based on the loss function, and then the parameters are updated layer by layer using methods such as gradient descent to minimize the loss function. The two processes are alternated until the optimal effect is achieved or the number of iterations is reached.

5 Simulation Results and Analysis

During the simulation process, the existing Case Western Reserve University (CWRU) rolling bearing dataset and Xi'an Jiaotong University bearing dataset were used as the training dataset [19]. The datasets were obtained from the Baidu PaddlePaddle dataset platform. After integrating the datasets, the training dataset and test dataset were allocated in an 8:2 ratio. The operating system was 64-bit Windows 11, with 16+512GB of computer memory, an RTX 3060 GPU model, and an Intel(R) Core(TM) i9-11900H processor model. The running environment was Python 3.6, based on the TensorFlow 2.1 and Keras framework. The same configuration was used to run the program in subsequent sections and will not be repeated. To fully test the effectiveness of the method proposed in this section, the effectiveness of the signal enhancement strategy proposed in this study was first tested, then the impact of the dynamic clipping mechanism proposed in this study on the performance of weak fault diagnosis was analyzed, and finally the performance of the overall model was tested, including the accuracy test for weak fault data of different degrees and the diagnostic effect test for compound early weak faults.

This paper takes the fault diagnosis of the inner ring of the walking mechanism bearing as an example for analysis. Figure 11 shows the frequency domain diagrams of the vibration and sound signals at a certain measurement point of the rolling bearing with an inner ring fault, as well as the frequency domain diagram of the enhanced signal. The amplitude ratio of the original sound signal at the rotation frequency is ES1/SA = 14.08, and the amplitude ratio at the fault characteristic frequency is ES2/SA = 2.57. The amplitude ratio of the original vibration signal at the rotation frequency is EV1/VA = 17.94, and the amplitude ratio at the fault characteristic frequency is EV2/VA = 5.41. The amplitude ratio of the enhanced signal at the rotation frequency is EE1/EA = 20.07, and the amplitude ratio at the fault characteristic frequency is EE2/EA = 7.42. At the rotation frequency, the amplitude ratio of the enhanced signal is 37.2% higher than that of the original sound signal and 13.4% higher than that of the original vibration signal, with an average increase of 25.26%. At the fault characteristic frequency, the amplitude ratio of the enhanced signal is 149.28% higher than that of the original sound signal and 31.67% higher than that of the original vibration signal, with an average increase of 98.23%. The amplitude ratio of the enhanced signal at the rotation frequency and the fault characteristic frequency is higher than that of the original vibration signal and sound signal, and it filters out the noise near the characteristic frequency, improving the signal quality.

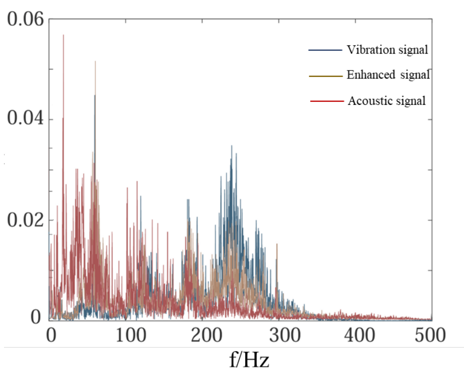

Fig. 11. Vibration frequency domain graph

To verify the diagnostic capability for inner ring faults in the walking mechanism, data from the 88th to 115th minute were selected as early fault data. These data were further divided, with the fault severity from the 88th to 92nd minute defined as fault level I, from the 93rd to 97th minute as fault level II, from the 99th to 103rd minute as fault level III, from the 105th to 109th minute as fault level IV, and from the 111th to 115th minute as fault level V. For each level, 2000 time-frequency graph samples were constructed for training and testing, with the data split into training and testing sets at a ratio of 7:3. The comparison results of different diagnostic models are shown in Fig. 12.

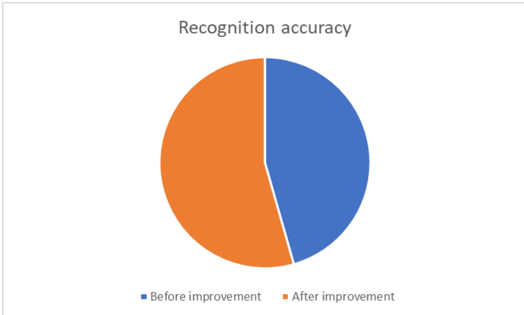

Fig. 12. Comparison of diagnostic results from different diagnostic models

From the comparison in the figure, it can be seen that the standard deviation of the fault diagnosis method based on a single source signal is at least 0.0207, and the variance of the accuracy of the ordinary multi-source fusion fault diagnosis method is at least 0.0182. This indicates that the existing single-source or multi-source fusion fault diagnosis methods are not stable enough in diagnosing early weak faults. However, the standard deviation of the accuracy of the method proposed in this study is 0.003, Compared with the existing early fault prediction methods, the method proposed in this paper has achieved significant optimization in numerical performance, thereby theoretically verifying its feasibility. Further, through the actual digital twin layout and the inspection and prediction during the operation process, this method can obtain prediction results closer to the real situation, providing a more reliable optimization solution for fault prediction.

6 Conclusion

This paper conducts research on the typical fault diagnosis and prediction of stacker cranes in the process of intelligent manufacturing, achieving the following results: Firstly, a digital twin of the target object is constructed, and through data mapping technology, the virtual-real correspondence relationship between the digital twin geometric model of the walking wheel mechanism and the physical entity is realized. By driving the data collected from the physical entity in real time, the identification and prediction results of bearing faults are reflected in the digital twin and the state operation curve of the stacker crane is output. Secondly, after receiving the fault vibration signal, the vibration frequency signal is processed by wavelet transform to generate a time-frequency image, which is then input into the 2D-CNN network to output the fault diagnosis and prediction results. Finally, a simulation experiment platform is built. In the experiment, the bearing fault data sets of Case Western Reserve University and Xi'an Jiaotong University are used as the training and test data sets. Through comparative experiments, it is verified that the method proposed in this paper can significantly improve the recognition accuracy and efficiency in bearing fault diagnosis and prediction. At the same time, there are also some research deficiencies in this paper, and these directions can be further studied in depth in the future.

The further research directions mainly focus on the following aspects: Firstly, conducting research on the diagnosis and identification of more complex fault types during the operation of stacker cranes. Given the limitations of the existing fault data sets in the field of stacker cranes, it is planned to collect more comprehensive fault data based on the actual operation of stacker cranes, with a particular emphasis on expanding the data set of the initial stage of faults to enhance the early warning capability for initial faults. Secondly, optimizing the fault diagnosis and prediction models for lightweighting. Since a large model volume and excessive parameters can lead to higher requirements for computer hardware and increased delay in the output of diagnostic results, how to effectively reduce the model volume and the number of parameters will become the key direction for model optimization. Finally, the theoretical model of the walking mechanism digital twin proposed in this paper needs to be further improved. By collecting more realistic operation data, the description accuracy of the physical entity of the walking wheel mechanism in the model can be enhanced; at the same time, the multi-dimensional theoretical model can be transformed into programming languages to build a digital twin system for the walking wheel mechanism, enabling the computer to automatically generate accurate and complete digital twin models based on real-time data, thereby achieving real-time mapping from the physical entity to the virtual space and meeting the real-time fault prediction requirements of the physical entity of the walking wheel mechanism.

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