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Intelligent Fault Diagnosis Algorithm for Mechanical and Electronic Systems Based on Structured Light Data

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Abstract: *In the current era of rapid technological development, modern mechanical equipment systems continue to move towards automation and intelligence, which puts higher demands on the technical performance of various aspects of the system. Structured light 3D intelligent cameras have been widely used in many fields such as artificial intelligence (AI) and industrial inspection due to their significant advantages of fast imaging speed and high accuracy. Structured light measurement is the process of measuring from multiple angles using a structured light measurement system to achieve a complete representation of the object being measured. However, the stitching of measurement data from multiple perspectives can have an impact on the completeness of the expression of the measured object. This article innovatively proposes an intelligent fault diagnosis algorithm for mechanical and electronic systems that combines deep learning (DL) technology. The algorithm deeply explores the feature information in structured light data and utilizes the powerful pattern recognition ability of DL to achieve accurate diagnosis of mechanical and electronic system faults. The results show that the algorithm proposed in this paper can effectively improve the efficiency and accuracy of fault diagnosis, providing strong support for ensuring the stable operation of mechanical and electronic systems.*

Keywords: *Structured light data, Mechanical and electronic systems, Intelligent fault diagnosis algorithms*

1. Introduction

In today's digital age, the wave of information technology is sweeping across the globe at an unprecedented speed, and the rapid development of AI technology has become the core force driving changes in various fields. With the continuous advancement of Industry 4.0 and intelligent manufacturing concepts, modern mechanical equipment is firmly moving towards automation, integration, and intelligence [1]. These advanced mechanical equipment bring efficiency and convenience to production, while their reliability and stability in operation have also become crucial considerations [2]. To ensure the healthy operation of these 'industrial brains', it is necessary to collect massive amounts of data to accurately reflect their health status. Carrying out status monitoring and diagnosis of mechanical equipment is like installing an "intelligent doctor" for mechanical equipment, which can timely detect, accurately diagnose, and scientifically predict potential faults [3]. This can not only effectively avoid production interruptions caused by sudden equipment failures, thereby reducing economic losses and operating costs, but also greatly reduce the risk of major accidents.

There is a very important practical need and significance for ensuring the continuity, stability, and personnel safety of production [4]. Structured light measurement technology, as an active optical measurement method, has attracted much attention in many fields such as reverse engineering, digital modeling, and computational measurement [5]. It cleverly obtains the three-dimensional information of the measured object by projecting encoded gratings, which is fundamentally different from traditional passive three-dimensional measurement techniques such as binocular stereo vision [6]. The core of structured light based 3D imaging lies in the measurement and reproduction of 3D parameters, which enables it to more accurately reproduce the true form of objects [7]. However, in practical applications, the quality of light stripe images can be affected by various factors such as the shape, material, and environment of the object being measured [8]. Therefore, how to quickly and accurately extract the center of the light strip has become the key to achieving high-precision measurement and the core issue in the research of line structured light sensors.

In recent years, DL theory has gradually become a hot learning algorithm in the field of machine learning (ML), especially in the field of image processing where remarkable achievements have been made. DL, with its powerful automatic feature learning ability, has also achieved significant success in the field of fault diagnosis. It can directly perform complex tasks such as target recognition, pose estimation, depth estimation. It is worth mentioning that in unstable measurement environments, DL does not rely on environmental and lighting conditions, which greatly improves the stability and reliability of measurements. Based on the above background, this article innovatively proposes an intelligent fault diagnosis algorithm for mechanical and electronic systems that combines DL technology. This algorithm deeply mines the feature information in structured light data, fully utilizes the powerful pattern recognition ability of DL, and achieves accurate diagnosis of mechanical and electronic system faults.

2. Application of DL in Intelligent Fault Diagnosis of Mechanical and Electronic Systems

2.1 DL

In the field of intelligent fault diagnosis of mechanical and electronic systems, traditional fault diagnosis methods mainly rely on fault feature extraction and pattern recognition [9]. Specifically, by conducting time-domain analysis on the vibration signals of mechanical equipment, we can understand the changing patterns of the signals over time; Frequency domain analysis can reveal the frequency components of a signal; Time frequency domain analysis combines the two to more comprehensively display signal characteristics [10]. Extract the fault features of each state from these analyses, input them into the classifier, and then complete the fault diagnosis. However, with the significant increase in computing power and the rapid development of computer vision technology, AI technologies such as DL have made breakthrough progress. In the field of fault diagnosis, DL algorithms that use vibration signals in one-dimensional and two-dimensional forms as network inputs have emerged in large numbers.

DL breaks the limitations of traditional ML based on shallow network structures and greatly enhances the ability to learn high-dimensional features. Compared with traditional methods, DL algorithm exhibits unique advantages in intelligent fault diagnosis of mechanical and electronic systems. It does not require manual complex feature engineering and can automatically learn fault features, greatly improving diagnostic efficiency and accuracy. Moreover, the DL model has stronger generalization ability and can adapt to the fault diagnosis needs under different working conditions, providing stronger guarantees for the stable operation of mechanical and electronic systems.

2.2 Specific Applications

Thanks to the rapid development of AI technology, data-driven intelligent fault diagnosis methods have become the mainstream of research in the field of fault diagnosis. Among them, Convolutional Neural Networks (CNNs), as a typical feedforward neural network, play a crucial role with their unique structure and computational methods. CNN achieves layer by layer extraction of topological features from input data by setting multiple filters in the network and using convolution and pooling operators. As the number of network layers increases, the extracted features become increasingly abstract, ultimately enabling the extraction of robust features with rotational and translational invariance from the original input data. A typical CNN mainly consists of three parts. Sample preprocessing is responsible for adjusting the input samples to meet the input requirements of CNN.

Feature extraction consists of multiple filtering stages, each of which includes a convolutional layer and a pooling layer. The convolutional layer convolves the local region of the input signal with the convolutional kernel, generating a nonlinear mapping under the action of the activation function; The pooling layer downsamples the convolutional results, reducing the amount of data while preserving key features. A typical CNN is shown in Figure 1. Sample classification adopts a multi-layer perceptron structure, consisting of one or more fully connected layers, with the last fully connected layer used for classification. Compared with traditional fault diagnosis methods, CNN based intelligent fault diagnosis methods do not require manual and carefully designed feature extraction processes, and can automatically learn effective features from large amounts of data, greatly improving diagnostic efficiency and accuracy. Moreover, the strong generalization ability of CNN enables it to better adapt to the fault diagnosis needs of mechanical and electronic systems under different working conditions, providing solid support for ensuring the stable operation of the system.

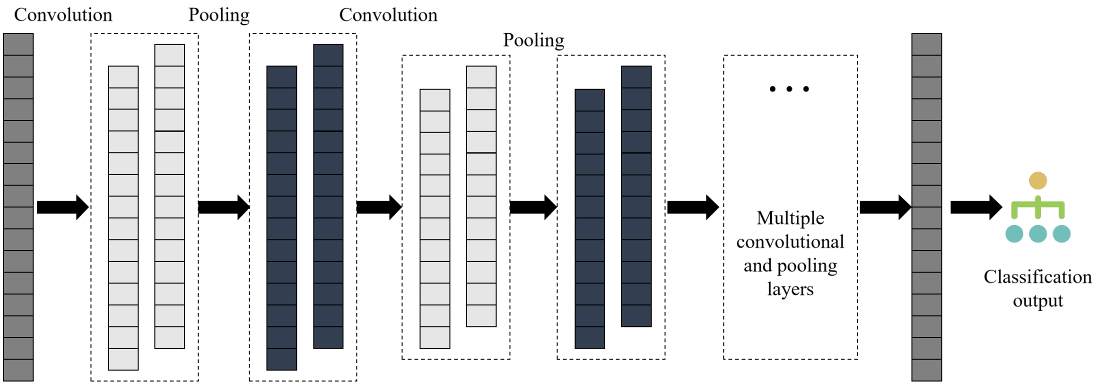

Figure 1 CNN structure

3. Algorithms and Experiments

3.1 Algorithm Principle

In monocular structured light systems, the projection process of the projection module can be regarded as the inverse operation of the camera imaging process. Specifically, the coordinates of a spatial point in the camera coordinate system can be determined through the principle of pinhole imaging; Correspondingly, the coordinates of a spatial point in the "imaging" coordinate system constructed by the projector can be characterized by its corresponding absolute phase value.

$$u_p = \frac{\phi(x, y) \times W}{2\pi N_v} \tag{1}$$

In this formula, u_p represents the horizontal coordinates of a spatial point on the projection plane; W represents the width of the projector image; N_v represents the number of periods of the stripes; And $\phi(x, y)$ represents the absolute phase value corresponding to the spatial point.

The result obtained by performing convolution operations on the current input for each convolutional kernel is used as input for the next layer of the neural network. Assuming that K_i^l, b_i^l represents the weight vector and bias of the i convolution kernel in the l layer, and x_j^l represents the value of the j local receptive field in the l layer, the convolution process can be expressed as:

$$y_i^l(j) = f\left(K_i^l * x^l(j) + b_i^l\right) \tag{2}$$

Among them, $*$ represents the convolution operator; $y_i^{l+1}(j)$ represents the output of the j neuron in the i feature surface in the $l+1$ layer; FF is the activation function.

The pooling layer is a key component that scales and maps the feature maps output by the previous convolutional layer. It performs downsampling operations to reduce the number of parameters in the network. In this process, commonly used pooling operations include max pooling and mean pooling. Specifically, max pooling selects the maximum value within the perceptual domain of each feature surface as the final output for that region, while mean pooling calculates the average value of all elements within the perceptual domain and outputs it. The formulaic expressions for these two pooling operations are as follows:

$$p_{l+1}^i(j) = \frac{1}{w} \sum_{i=(j-1)w+1}^{jw} a_l^i(t) \tag{3}$$

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$$p_{l+1}^{i}(j)=\max_{(j-1)w+1\leq t\leq jw}\left\{a_{l}^{i}(t)\right\} \tag{4}$$

Among them, $a_l^i(t)$ represents the activation value of the t neuron in the i feature plane of the l layer, w represents the width of the pooling region, and $p_{l+1}^i(j)$ is the pooled value corresponding to a certain neuron in the $l+1$ layer.

During supervised training, we simultaneously optimize feature extractor G_f and classifier C. The source domain dataset consists of raw data $\{X_s, Y_s\}$, where X_s is the source domain data and Y_s is its corresponding label; The target domain dataset $\{X_t\}$ only contains unlabeled target domain data X_t. During training, the source domain data X_s is first input into the feature extractor G_f to extract high-dimensional feature representations of the data. Subsequently, these features are further input into two independent classifiers C_1, C_2. The task of these two classifiers is to accurately classify the source domain data into K categories (where K is the total number of categories in the source domain). The classifier uses the Softmax function as the output layer to obtain the probability distribution on each category. The classification loss function is:

$$L_{cls}(X_s,Y_s)=-E_{(x_s,y_s)\sim(X_s,Y_s)}\sum_{k=1}^{K}1_{[k=y_s]}\lg p(y\mid x_s) \tag{5}$$

In the formula, $p(y \mid x_s)$ corresponds to the probability output of the classifier on the source domain samples.

3.2 Experimental Result

To verify the effectiveness of the algorithm proposed in this paper, a comparative experiment will be conducted between the algorithm proposed in this paper and traditional algorithms based on BP neural network (BPNN). The experiment used the same mechanical and electronic system fault dataset to train and test the proposed CNN based fault diagnosis model and the traditional BPNN based fault diagnosis model separately. Figure 2 shows the accuracy comparison results of two algorithms on the test set. From the figure, it can be seen that the CNN based algorithm proposed in this paper significantly outperforms the traditional BPNN algorithm in terms of fault diagnosis accuracy. This result fully demonstrates the superiority of the algorithm proposed in this paper. The main reason for the performance improvement of the algorithm in this article is that CNN can automatically learn more effective fault features from the original structured light data. Traditional BPNN relies on manual feature extraction, which is not only time-consuming and labor-intensive, but also difficult to capture deep level information in the data. By stacking convolutional and pooling layers, CNN can automatically extract local and global features of data, thus better characterizing the fault states of mechanical and electronic systems. In addition, CNN also has strong robustness and can effectively deal with noise and interference in structured light data, further improving the accuracy of diagnosis.

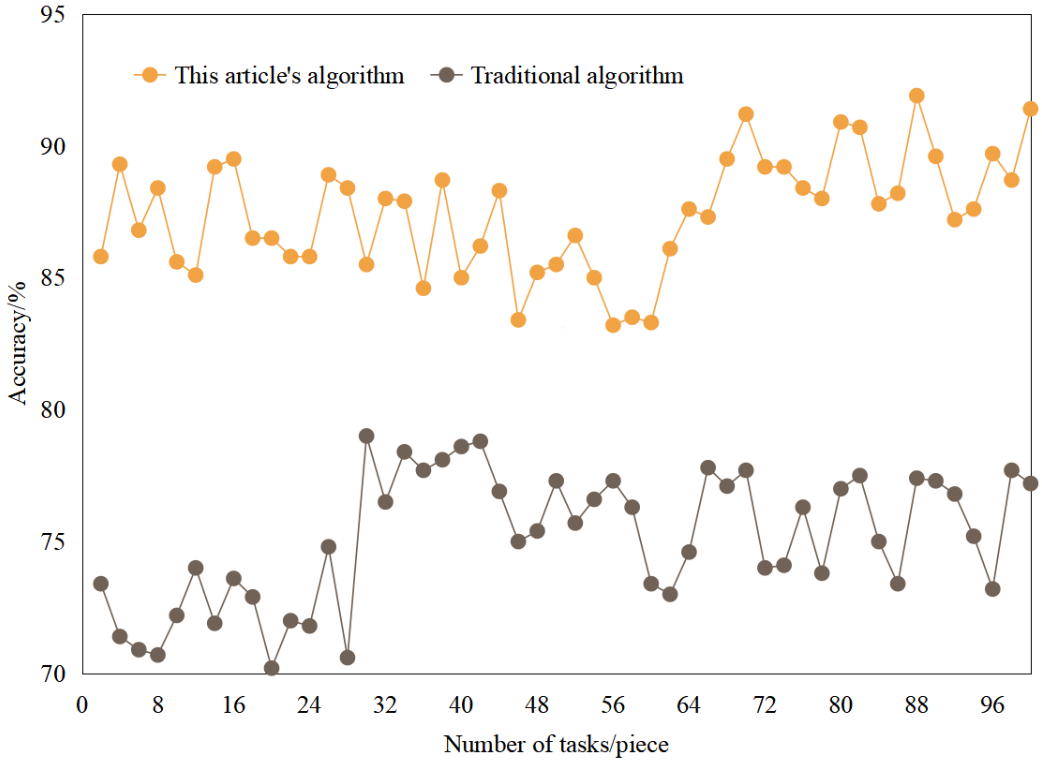

Figure 2 Accuracy comparison

4. Conclusions

Traditional intelligent fault diagnosis algorithms face many challenges in practical applications. It relies on manual feature extraction and expert knowledge, making it difficult to adapt well to different scenarios in the complex and changing working environment and conditions of mechanical and electronic equipment. Once the operating conditions of the equipment change, the diagnostic accuracy and efficiency of traditional algorithms will be greatly reduced. In contrast, this article innovatively proposes an intelligent fault diagnosis algorithm for mechanical and electronic systems that combines CNN technology. This algorithm deeply mines the feature information in structured light data, and with the powerful feature extraction ability of CNN, accurately diagnoses mechanical and electronic system faults. The experimental results show that the algorithm significantly improves the accuracy of fault diagnosis, effectively ensures the stable operation of mechanical and electronic systems, and provides new ideas and technical support for the intelligent development of related fields.

However, the algorithm presented in this article also has certain limitations. On the one hand, the dependence on a large amount of high-quality structured light data is high, and the cost and difficulty of data acquisition are high. If the data volume is insufficient or the quality is poor, it will affect the algorithm performance. On the other hand, algorithm models are relatively complex, consume large amounts of computing resources, and have low efficiency when running on devices with limited hardware configurations. In the future, we plan to further optimize algorithms, reduce dependence on data volume, improve the lightweighting of models, and enable them to be efficiently applied in more scenarios, continuously promoting the development of intelligent fault diagnosis technology for mechanical and electronic systems.

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