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Pellet Size Detection and State Analysis based on Machine Vision and Intelligent Algorithm

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Abstract

Aiming at the accuracy and efficiency of pellet size detection and state analysis in the process of iron and steel smelting, this paper proposes a solution based on machine vision and intelligent algorithm. The pellet images are collected by high-resolution camera equipment, and the particle size is automatically detected by convolutional neural network (CNN) model. At the same time, combining time series analysis and state space modeling, real-time monitoring and prediction algorithm is designed to quantify the relationship between pellet size and operation parameters. The experimental results show that the accuracy of particle size detection is more than 93%, and the production parameters can be adjusted in real time, which significantly improves the production efficiency and product quality. This study provides technical support for the intelligent upgrading of the iron and steel smelting industry, and lays a foundation for the optimization and expansion of the application of subsequent intelligent algorithms.

Keywords

Pellet Size; Automatic Detection; Prediction Algorithm.

1. Introduction

Iron and steel industry as an important pillar of the national economy, its production efficiency and product quality directly affect the national industrial strength. In the process of iron ore smelting, pellet is the key intermediate product, and its particle size distribution plays a crucial role in the stability of the subsequent process and the performance of the final product. However, the traditional pellet size detection method has the problems of poor accuracy, low efficiency and high cost, which seriously restricts the high-quality development of iron and steel industry.

To solve these problems, the steel industry is in urgent need of an efficient, accurate and cost-effective pellet size detection scheme. With the rapid development of computer vision and artificial intelligence technology, new solutions are provided. These technologies can rapidly process and extract features from pellet images, providing a new method and possibility for particle size detection.

Based on computer vision and artificial intelligence technology, a new method of pellet particle size detection and state analysis is proposed in this study. By constructing advanced image processing algorithms and intelligent prediction models, this method can automatically and quickly identify particle size features in pellet images to achieve accurate particle size detection and classification[1]. The experimental results show that the proposed method is superior to the traditional detection

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methods in terms of accuracy, efficiency and cost, and can provide a reference for the intelligent development of iron and steel industry.

2. System Structure

The system is composed of five core modules, which constitute a complete pellet particle size detection and state analysis system. Each module collaborates to ensure efficient and real-time pellet size detection, state analysis and production parameter optimization. Specific modules include:

2.1 Data Acquisition Module

The pellet image data is collected by high resolution camera in real time and transmitted to the data storage system by image processing interface. Equipped with appropriate lighting and camera arrangement to ensure image quality and obtain high-quality raw data.

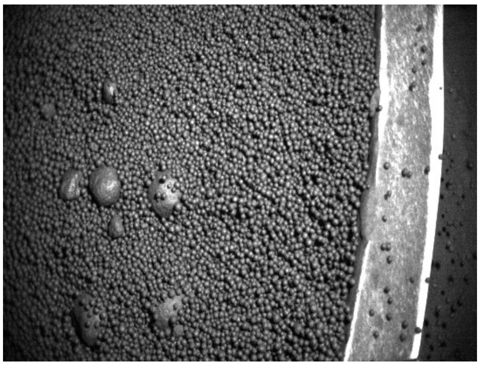

Fig. 1 Steel plant field acquisition images

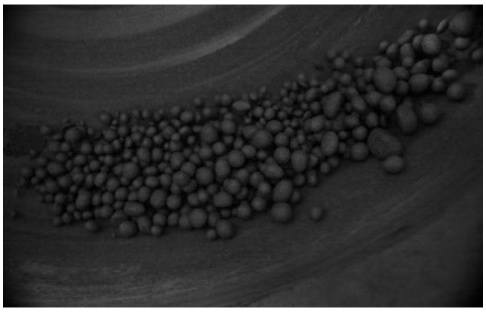

Fig. 2 Experimental pellet image

2.2 Page Numbers

In order to improve the accuracy and repeatability of measurement results, light intensity sensors and temperature sensors are used to measure deposition height and ambient temperature at different times during the sedimentation of sample particles. The particle size distribution of the measured sample is finally obtained through dynamic analysis of the collected data such as height and temperature[2]. Convolutional neural network (CNN) was used to process and analyze the collected pellet image, and the particle size, shape and other key features of the pellet were identified.

2.3 Status Analysis Module

The state analysis module is based on the time series analysis method and combines the real-time data in the production process (such as temperature, pressure, conveying speed, etc.) to deeply analyze the relationship between pellet size and various production operation parameters. Through state-space modeling technology, the module is able to monitor the changing trend of pellet size in real time, predict the potential production state, and evaluate the impact of these changes on the production process. This analysis not only helps optimize production parameters, but also identifies potential

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problems in advance, providing strong support for smooth operation and quality control of the production process.

2.4 Feedback Control Module

The feedback adjustment module adjusts the production parameters (such as raw material ratio, furnace temperature, air volume, etc.) in real time according to the output of the particle size detection and condition analysis module to ensure that the production process is maintained in the best condition. By utilizing machine learning and optimization algorithms, the module is able to automatically adjust key production parameters for particle size control and continuous optimization of the production process. This closed-loop control method not only improves the production efficiency, but also ensures the consistency of product quality, and contributes to the stability of the production process and the efficient use of resources.

2.5 Real-time Monitoring System

A visual interface allows operators to monitor pellet size and production status in real time. The system can track all parameters in the production process in real time, and issue early warnings in case of anomalies, alerting operators to potential problems. In addition, when the system detects anomalies or optimization needs, it can also provide adjustment suggestions or automatically implement optimization measures according to preset rules, ensuring the stability and efficiency of the production process.

3. System Design and Implementation

3.1 Data Acquisition and Preprocessing

In order to ensure the accuracy and reliability of pellet size detection and state analysis, this study will use high-performance camera equipment to collect high-resolution images of pellets in the actual production environment. These camera devices will be precisely configured to capture various physical characteristics of the pellets, including but not limited to size, shape, surface quality, and more. The camera system will be equipped with advanced automatic exposure and focus adjustment functions to cope with possible lighting changes and pellet movement in the production environment. In addition, the application of high dynamic range (HDR) and anti-shake technology will further improve image quality and reduce image blur and distortion caused by environmental factors[3]. In order to obtain a sufficiently diverse data set, image acquisition will be carried out over different time periods and under different production conditions to cover the variety of morphology and characteristics that may occur in pellets.

The collected original image data often contains various noise and interference information, which will affect the subsequent feature extraction and model training. Therefore, we need to perform a series of pre-processing steps to improve image quality before entering data into the particle size detection model[4].

Noise removal: The use of Gaussian filter, mean filter and other filters to remove noise in the image. These filters can smooth the image, reduce the interference of random noise, and make key features in the image more prominent. The formula is:

$$G(x,y)=\frac{1}{2\pi\sigma^2}\exp(-\frac{x^2+y^2}{2\sigma^2}) \tag{1}$$

Where σ is the standard deviation and controls the smoothness of the filter.

Contrast enhancement: Enhance the contrast of the image through histogram equalization and other methods. Contrast enhancement can make the difference between light and dark in the image more

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noticeable, helping to highlight the edge and texture features of the pellets. Adjust the distribution of pixel values by the following formula:

$$S = T(R) \tag{2}$$

Where R is the pixel value of the input image, T(R) is the mapping function after histogram equalization, and S is the enhanced pixel value of the output image.

Brightness adjustment: Adjust the brightness according to the lighting conditions of the image. Brightness adjustment ensures that key features in the image remain visible in different lighting conditions, avoiding feature loss or distortion due to insufficient or excessive light. The formula is:

$$Inew(x,y) = \alpha \cdot I(x,y) + \beta \tag{3}$$

Where, α is the brightness factor, β is the brightness offset, and I(x,y) is the brightness value of the original image.

Through the above pre-processing steps, we can obtain more clear and accurate pellet image data, which lays a solid foundation for the subsequent feature extraction and model training.

3.2 Particle Size Detection Model

We will design a CNN model that includes multiple convolution layers, pooling layers and fully connected layers. The convolution layer is responsible for extracting local features in the image, such as edges and textures. The pooling layer is used to reduce the dimension of the feature map, reduce the computational effort, and retain important information. The fully connected layer maps the extracted features to the sample label space to achieve granularity classification. Pooling operations such as maximum pooling are performed by the following formula:

$$P\max(x,y) = \max(I(x,y), I(x+1,y), I(x,y+1), I(x+1,y+1)) \tag{4}$$

In order to ensure the generalization ability and accuracy of the model, we will use cross-validation and other techniques to train and verify the model. Through several iterations of training, the model structure and parameters are constantly adjusted until the model achieves satisfactory performance on the verification set. After the training is completed, the model will be able to classify the granularity of the new pellet image. For the input pellet image, the model will automatically extract its feature representation and output its corresponding particle size label through the fully connected layer. In this way, we can achieve rapid and accurate detection of pellet size.

3.3 State Analysis Model

The prediction model of pellet state was constructed by time series analysis and regression analysis. These models will be able to predict future state trends of pellets based on inputs such as current particle size and operating parameters. In the process of model construction, we will fully consider the complexity and variability of pellet state, and adopt appropriate model structure and parameter Settings to ensure the accuracy and reliability of prediction [5]. The formula is as follows:

$$\beta = (XTX) - -1XTX \tag{5}$$

Where, X is the input eigenmatrix, Y is the target variable vector and β is the coefficient vector.

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Through the state prediction model, we can understand the changing trend of pellet state in advance and provide powerful data support for the optimization and control of the production process[6]. For example, when the pellet state is predicted to be abnormal, we can timely adjust the production parameters or take other measures to avoid the occurrence of problems, so as to ensure the stability of the production process and the consistency of product quality.

4. Experiment and Result

4.1 Particle Size Detection Performance

The CNN particle size detection model in this study performs very well on the test set, reaching an accuracy of more than 90%. By training and testing 10,000 images of pellets from different production conditions, the model was able to accurately identify pellets of different particle sizes, ranging from fine particles to large pellets. During the experiment, we used confusion matrix and ROC curve to evaluate the performance of the model. The results show that the model has high recognition accuracy and strong discrimination ability in each particle size category. In terms of processing efficiency, the system is able to process more than 10 images per second with a response time of less than 1 second, ensuring the need for real-time monitoring, as shown in Table 1.

Table 1. Summary of key performance data of pellet size detection CNN model

Item	Details
Model	CNN particle size detection model
Test set accuracy	Over 90%
Number of training and testing images	10,000 images (pellet images from different production conditions)
Covering size level	Fine particles to large pellets
Evaluation method	Confusion matrix, ROC curve
Processing efficiency	Processing more than 10 images per second

As can be seen from Table 1, the model not only performs well in accuracy, but also has sufficient processing speed and real-time performance in practical applications to meet the real-time detection requirements of the production line.

4.2 State Analysis and Optimization Effect

The application of the system in the actual production environment shows remarkable optimization effect. Through real-time monitoring of pellet size and state analysis, the system can dynamically adjust operating parameters (such as temperature, humidity, material ratio, etc.) during the production process. Field tests show that the system can optimize the production parameters according to the test results, reduce the production of unqualified products, and improve the production efficiency.

During a week of continuous testing, the system successfully helped the production line reduce energy consumption by about 15%, while the product acceptance rate increased by 5%. In addition, feedback from production personnel shows that the system significantly reduces the work intensity of manual inspection, improving the overall production efficiency and product quality consistency.

Through these experimental results, it is proved that the pellet size detection and state analysis system based on machine vision and intelligent algorithm is efficient and reliable in actual production, and provides important technical support for the intelligent upgrading of iron and steel smelting industry.

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5. Conclusion

The pellet particle size detection and state analysis system based on machine vision and intelligent algorithm proposed in this study uses high-resolution image acquisition, convolutional neural network (CNN) model and state analysis technology to realize high-precision automatic detection of pellet size and optimization of production process. The experimental results show that the fully trained and verified CNN particle size detection model has a recognition accuracy of more than 90% on the test set, which shows high model performance and practical application value. By accurately identifying pellet size information, the system can provide real-time feedback for parameter adjustment during the production process, thereby optimizing production efficiency and product quality. In the stage of system integration and field test, the stability and accuracy of the system have been fully verified by comparing with the actual production data. Field test results show that the average response time of the system is less than 1 second, the processing speed is more than 10 images per second, and the detection accuracy rate is more than 90%, which fully proves the excellent performance of the system in the actual production environment. The feedback of production personnel also shows that the system greatly improves the production efficiency, reduces the labor intensity and cost of manual detection, and is simple to operate, easy to integrate and use[7].

In summary, this study successfully developed a pellet size recognition and state estimation system based on machine vision and intelligent algorithm, which has significant advantages in improving production automation, reducing manual intervention, and improving production efficiency and product quality. Its application in the steel smelting industry has a broad prospect, provides a strong technical support for the intelligent upgrading of the industry, and has a high practical promotion value.

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