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SIMULATION INSPECTION TECHNOLOGY FOR SURFACE CHARACTERISTICS OF HIGH-QUALITY STRIPS

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Abstract
To address the challenge of high rejection rates due to surface quality defects that are hard to detect with the naked eye, a comprehensive model was developed for detecting such defects and implemented a full-fledged equipment and system for surface quality inspection. Specifically, a targeted comprehensive model was formulated to identify three types of plate and strip surface quality defects. Furthermore, the latest hardware equipment and an advanced unsupervised self-learning algorithm were integrated into the detection system to enhance the identification and classification of these surface quality defects. The results demonstrate an improvement in the comprehensive detection rate and classification accuracy of surface defects from 96 % and 91 % to 98 % and 95 %, respectively. Moreover, the qualified rate of finished products has increased from 94 % to 99 %, leading to improved accuracy in defect detection and a significant decrease in false alarm rates. These findings provide a solid foundation for significantly reducing material waste and enhancing the overall quality of the production process.
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Key Words: Strip Rolling, Surface Quality, Defect Identification, Deep Learning

1. INTRODUCTION

In recent years, with the high-quality development of the international steel industry, increasing attention has been paid to the environmental friendliness, intelligence, and digitalization of high-end plate and strip products. However, due to limiting factors such as production process technology and on-site operating environment, the types and frequency of surface quality defects in plate and strip products have been increasing during the actual production process. These defects include warping, scratches, and surface cracks in hot-rolled strip steel, as well as scratches, pits, bright lines on the edges of cold-rolled strips, pitting, colour difference, and serious scratches on the coating production line. The pursuit of efficiency and speed in current production lines sometimes results in hidden or difficult-to-detect defects, which exert significant pressure on product quality and reputation within the factory.

Currently, the inspection of surface quality in plate and strip products heavily relies on manual observation and on-site production experience. However, external environmental factors such as lighting conditions and operator fatigue contribute to inaccuracies, leading to a detection and identification rate that does not meet the required high accuracy and low error requirements [1]. The detection of surface defects has been applied in different fields including railway parts inspection, additive manufacturing process surfaces, and cutting surfaces [2]. As the field continues to expand, numerous detection methods have emerged, and traditional contact identification detection is slowly being replaced by laser detection and non-contact scanning detection [3]. Generally, non-destructive evaluation of surface fracture defects uses a non-contact method of scanning laser spots, but this technology can only be applied to objects with a certain size [4, 5]. More advanced laser measurement technology can already control the accuracy of contour data to about 50 μm [6]. However, it can only be applied to strips with a width of 100 mm, and the production process parameters are also somewhat different from those used in actual production. Another method is to use 3D point clouds with a certain accuracy to perform quality inspection during the manufacturing process [7, 8]. However, obtaining high-quality 3D point clouds continuously on the strip steel used for surface quality inspection of plate and strip rolling is difficult due to the harsh conditions of the production environment. In order to address the limitations of previous research, this study will employ a non-contact camera scanning identification detection method and fully leverage the effectiveness of the self-learning algorithm combined with simulation to targetedly improve the detection rate and accuracy of the surface defect detection of the inspection system in all specifications and all working conditions [9, 10].

The research achievements regarding surface quality defect detection systems for high-quality strips have been widely applied across various industries [11]. Nevertheless, the automatic inspection equipment currently utilized on numerous production lines still falls short of meeting the demand for high precision. To address this issue, this paper establishes a surface quality defect model, introduces a simulation-based control methodology, and develops a comprehensive surface quality inspection equipment and system. This system leverages feedback from detected information to regulate and ensure superior surface quality.

2. STATE OF THE ART

The quality inspection of strip steel surfaces typically involves the cross-fusion of multiple disciplines and, at the same time, necessitates a cohesive integration of theory and application. The detection accuracy of the systems involved in current research is not high and cannot meet the current high-quality and high-level development requirements of strip steel. There is a certain accuracy gap at both the detection input and output ends. Molleda et al. [12] conducted more in-depth research on the three-dimensional imaging visualization technology of the detection system and the improved calibration of machine vision equipment. However, there remains room for improvement in the modelling and solver components, resulting in suboptimal accuracy. Siyamalan [13] proposed a collaborative semi-supervised deep learning method based on knowledge distillation for defect detection, aiming to improve the classification performance under semi-supervised learning with limited labelled training data. However, this method requires additional unlabelled data, and the impact of unlabelled data on the accuracy of surface defect detection is negative; the lack of data reduces the accuracy of the model. Nooralishahi et al. [14] proposed a self-training image segmentation method for images collected during thermal imaging inspection of industrial parts, utilizing a wireless supervised model to segment images based on local thermal patterns. However, the accuracy of this method in detecting surface defects is inadequate and cannot meet the accuracy requirements for surface defect detection.

Most similar studies have certain deficiencies in their algorithms and models. These algorithms need to keep pace with the requirements of strip steel inspection. Zeiler et al. [15] proposed an algorithm to segment the strip edge image into polished areas, fracture areas, defective fracture areas, and burrs. However, this algorithm can only identify and detect strip edge defects and has not been extended to the overall surface of strip steel. Maciáas et al. [16] judged the consistency among the models and their accuracy by comparing thickness and temperature flux profiles measured in plant against predicted ones, but there is a lack of in-depth research on models and algorithms, and the identification and classification of defects is relatively simple. Ding et al. [17] used eXplainable Artificial Intelligence (XAI) machine learning technology for more accurate detection and decision-making, but their research content only focuses on the development of algorithm technology for common defects. The surface quality detection algorithm is more complex and diverse than the defects under study. Overall, the research on algorithms and models is not comprehensive enough. Kumaresan et al. [18] used VGG16 and ResNet50 as the basic models of an enhanced set to study the classification of weld defects under deep learning, resulting in improved accuracy to a certain extent. However, the algorithm and modelling limited the comprehensiveness of the method, and it could not be generalized for the detection of strip steel. Furthermore, the method could not be combined with simulation results or verified by practical applications. Similarly, Ibrahim and Tapamo [19] proposed an innovative method using deep learning technology, specifically using a part of the pre-trained VGG16 model as a feature extractor and a newly developed convolutional neural network (CNN) as a classifier. However, this study focused too much on the accuracy of the algorithm. The dataset used in the study was relatively small and contained a limited number of classes. Furthermore, the model algorithm also has shortcomings in simulation and application.

Conventional detection accuracy is relatively low, unable to meet the high-precision requirements of high-quality steel strips. The surface quality inspection of steel strip rolling lacks a comprehensive technology and application that integrates high precision, strong correlation, advanced algorithms, and models. Therefore, in order to improve the detection and application level of surface quality inspection for high-quality steel strips, this paper introduces a method that combines surface quality defect simulation models, numerical simulations, and AI-driven deep learning defect recognition algorithms, aiming to achieve the integration of theory, simulation, and practical research. This approach provides a comprehensive framework for advancing surface quality inspection methods to address the issue of steel strip surface defect detection.

3. METHODOLOGY

3.1 Establishment of defect definition model of surface quality

There are numerous types of surface quality issues encountered in plate and strip products, each stemming from different causes. To better categorize and address these defects, three judgment models will be established within the system. The creation of the surface quality defect setting model will not only provide a clearer prediction direction for the surface inspection system but also offer theoretical control measures and guidance for mitigating defects in finished strips. This approach ensures a comprehensive and targeted strategy for identifying and resolving surface quality issues.

Scratch determination model: The scratch judgment setting model utilizes a scratch comprehensive judgment index. A lower value of this index indicates a decreased likelihood and severity of scratches, while a higher value suggests an increased probability and severity of their occurrence [20].

$$\lambda = \frac{1}{4\mu}\left(\sqrt{\frac{\Delta h}{R'}} + \frac{T_0 - T_1}{P}\right) \cdot V^{\alpha} \tag{1}$$

$$R' = R\left[1 + \frac{C_0 P}{b\Delta h}\right] \tag{2}$$

$$C_0 = \frac{16(1 - {v_R}^2)}{\pi E_R} \tag{3}$$

where λ represent the comprehensive scratch judgment index; μ is the coefficient of friction; R' is the flattened radius of the work roll; Δh is the reduction amount; T_0 is the back tension; T_1 is the front tension; P is the total rolling pressure; V is the rolling speed; α is the velocity influence index; C_0 is the material coefficient; b is the strip width; R is the work roll radius; v_R is the work roll Poisson ratio; E_R is the work roll elastic modulus.

Edge-bright-line determination model: In the finished steel strip, narrow bright lines with shadow colour occasionally appear near the edge. This part is clearly distinguished from other positions of the strip. Through the study of bright lines, it was found that the main source of defects in edge bright lines is the plate shape problem. The unevenness of the plate shape in the transverse and longitudinal directions leads to the generation of edge bright lines. As a result, the lateral distribution of plate shape serves as a key determinant for identifying edge bright lines.

$$\sigma_1(y) = \bar{\sigma}_1 + \frac{E}{1-v^2}\left[1 + \frac{h(y)}{h} - \frac{H(y)}{H} - \frac{L(y)}{L} + u'(y) - \frac{\Delta b}{b}\right] \tag{4}$$

$$\sigma_0(y) = \bar{\sigma}_0 + \frac{E}{1-v^2}\left\{\frac{h(y)H\left[1+u'(y)\right]}{h \times H(y)\left[1+\dfrac{\Delta b}{b}\right]} - \frac{L(y)}{L}\right\} \tag{5}$$

where $\sigma_1(y)$ is the transverse distribution of front tension; $\overline{\sigma_1}$ is the total front tension; $\sigma_0(y)$ is the transverse distribution of rear tension; $\overline{\sigma_0}$ is the total rear tension; E is the modulus of elasticity; v is the Poisson ratio; $h(y)$ is the distribution of exit thickness; h is the average exit thickness; $H(y)$ is the distribution of entrance thickness; H is the average entrance thickness; $L(y)$ is the distribution of entrance length; L is the average entrance length; Δb is the absolute width expansion amount; b is the width of the steel strip; $u'(y)$ is the lateral displacement increment distribution.

Quality setting model of surface roughness: The surface roughness formula for the finished plate strip is incorporated into the plate surface roughness quality setting model [21], where it is combined with research work on numerical simulation to further broaden and deepen the application of the surface quality detection system.

$$Ra_{strip} = K_{ss} \cdot Ra_{ge} + K_{rs} \cdot Ra_r \tag{6}$$

$$K_{ss} = \eta_{ssr} \cdot \eta_{ssh} \cdot \eta_{ssk} \cdot \eta_{ssp} \cdot g(\varepsilon) \tag{7}$$

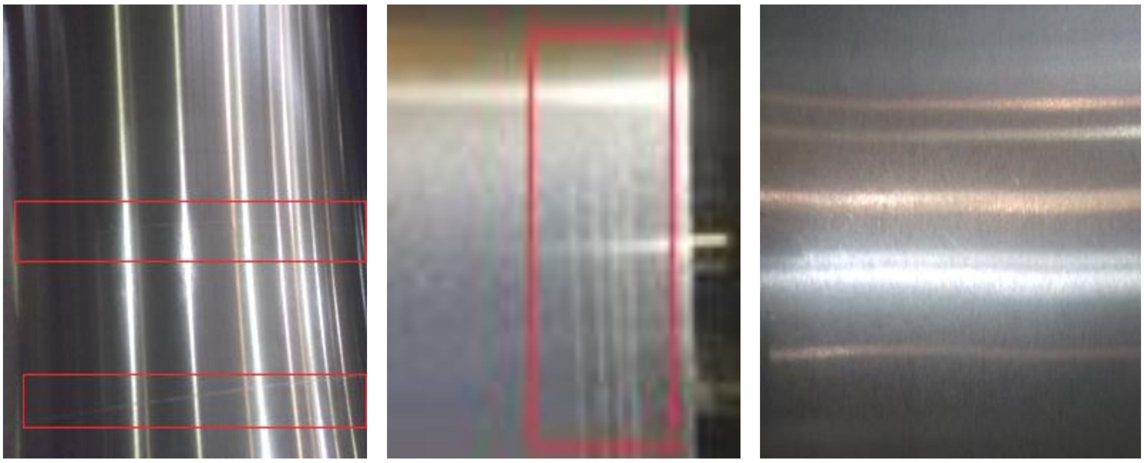
$$K_{rs} = \eta_{rsr} \cdot \eta_{rsh} \cdot \eta_{rsk} \cdot \eta_{rsp} \cdot f(\varepsilon) \tag{8}$$

where Ra_{strip} represents the surface roughness of the finished strip steel; K_{ss} is the heredity rate of the surface roughness of the strip steel from the upstream stand; Ra_{ge} is the surface roughness of the strip steel at the entrance of the last stand; K_{rs} is the imprint rate; Ra_r is the surface roughness of the work roll; η_{ssr} is the coefficient of influence of the roll surface properties on the heredity rate; η_{ssh} is the coefficient of influence of the strip's entrance thickness on the heredity rate; η_{ssk} is the coefficient of influence of the strip's strength on the heredity rate; η_{ssp} is the coefficient of influence of the variation in average rolling pressure caused by fluctuations in lubrication conditions on the heredity rate; ε is the reduction amount; η_{rsr} is the coefficient of influence of the roll surface properties on the imprint rate; η_{rsh} is the coefficient of influence of the strip's entrance thickness on the imprint rate; η_{rsk} is the coefficient of influence of the strip's strength on the imprint rate; η_{rsp} is the coefficient of influence of the variation in average rolling pressure caused by fluctuations in lubrication conditions on the imprint rate.

$$P(S) > P(E) > P(R) \tag{9}$$

where $P(S)$ is the scratch judgment priority; $P(E)$ is the edge bright line judgment priority; $P(R)$ is the board surface roughness judgment priority.

Fig. 1 displays the defect maps corresponding to the three judgment models. These models efficiently categorize numerous defect issues into broader categories. Each model functions as a dedicated channel for defect detection, and they are prioritized and weighted in the sequence of scratches, edge highlights, and surface irregularities, based on the importance and severity of the defects. Importantly, the surface quality defect setting model also requires the provision of theoretical solutions for defect management, hence the priority setting takes into account the criticality of late-stage defect management control. Eq. (9) establishes the model channel priority order within the detection system. Additionally, Fig. 2 illustrates a schematic diagram outlining the process for setting the channel priority of the model.



a) b) c)

Figure 1: Actual defect morphology maps; a) scratch defect; b) edge bright line defect; c) roughness chromatic aberration defect.

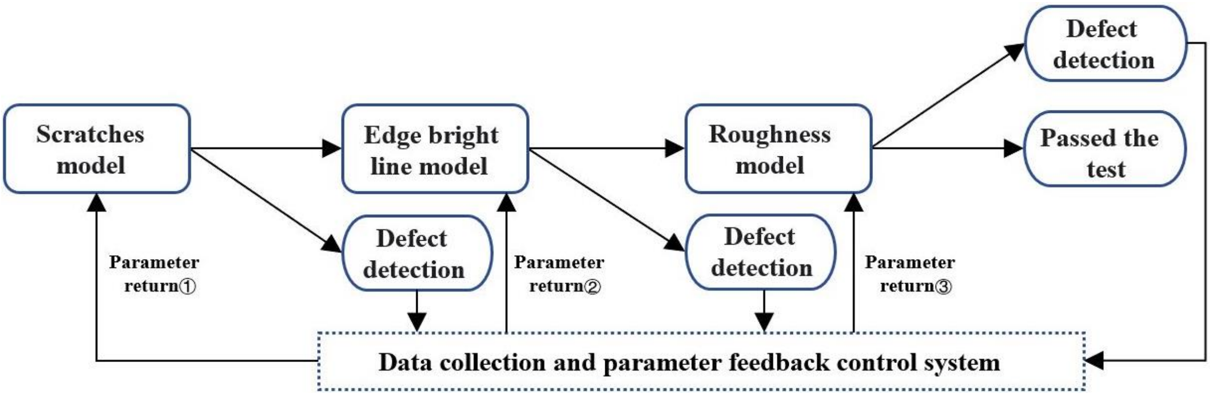


Figure 2: Schematic diagram of the surface inspection system process (the number is the priority order of parameter return control).

3.2 Equipment and system for surface quality inspection

Imaging system and equipment: The comprehensive surface quality inspection system integrates cutting-edge technologies from optics, mechanics, electronics, as well as computer software and hardware. It encompasses a broad spectrum of disciplines, including computer science, image processing, pattern recognition, artificial intelligence, signal processing, and optomechatronics. This seamless integration results in a robust surface quality defect management system, comprising four core components: imaging technology, processing algorithms, computational platforms, and industrial applications. Fig. 3 illustrates the holistic structure of the surface quality defect detection system.

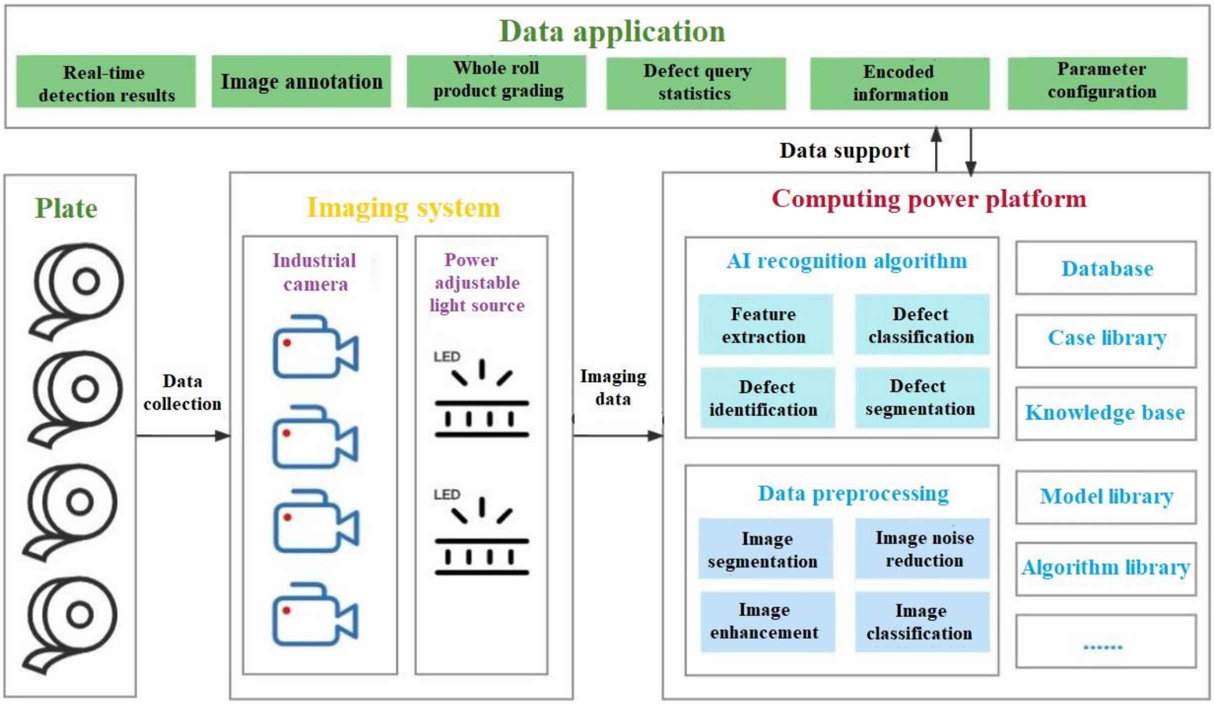


Figure 3: Schematic diagram of the surface inspection system process.

The imaging system serves as a vital bridge, connecting sheet product data acquisition with algorithm-driven imaging data processing on the platform. To support data-centric applications, the on-site collection database fulfils crucial functions such as real-time display of inspection results, image annotation, comprehensive grading of entire roll products, defect query statistics, coding information retrieval, and parameter configuration. The system's core hardware comprises an image acquisition system, which is centred around industrial cameras, adjustable industrial light sources, and high-precision, adjustable camera mounts. Furthermore, it incorporates a mechanical structure system that includes air cooling devices, camera protection enclosures, mechanical frames, and camera adjustment mechanisms. Additionally, the system is complemented by an upper computer software system, which consists of upper computers, printers, terminal alarms, storage servers, and an image processing server.

Processing algorithms: The scarcity of data leads to low accuracy in algorithms, necessitating lengthy data collection efforts that traditional algorithms cannot satisfy. Therefore, given the specificity of on-site production, research and development have been undertaken in the realm of unsupervised learning, utilizing deep learning technology for defect detection. This approach involves modelling using a large amount of positive sample data from the industry to identify and extract anomalous data. Subsequently, the model for recognizing anomalous data is continuously iterated and enhanced to achieve higher precision and faster implementation.

Initially, the imaging system and equipment are used to detect defects, obtain defect data, and filter out images of significant defects. These defect images are then stored in a storage server. The subsequent step involves defect localization and classification, utilizing annotation data from the previous stage and a deep neural network based on the AlexNet architecture. This architecture typically comprises an input layer with a larger amount of information, five convolutional layers, and three fully connected layers, utilizing activation functions to introduce non-linearity and enhance convergence speed [22]. However, due to the limited detection categories and high computational cost, the original AlexNet model has been optimized into a new model featuring four convolutional layers, pooling layers, and three fully connected layers, as depicted in Fig. 4 [23].

The detection model undergoes unsupervised self-learning training using a designated key dataset, enabling it to identify specific defect coordinates and their corresponding categories. Additionally, the AI model undergoes continuous training and refinement through data accumulation, resulting in steady improvements in both the defect recognition rate and detection accuracy.

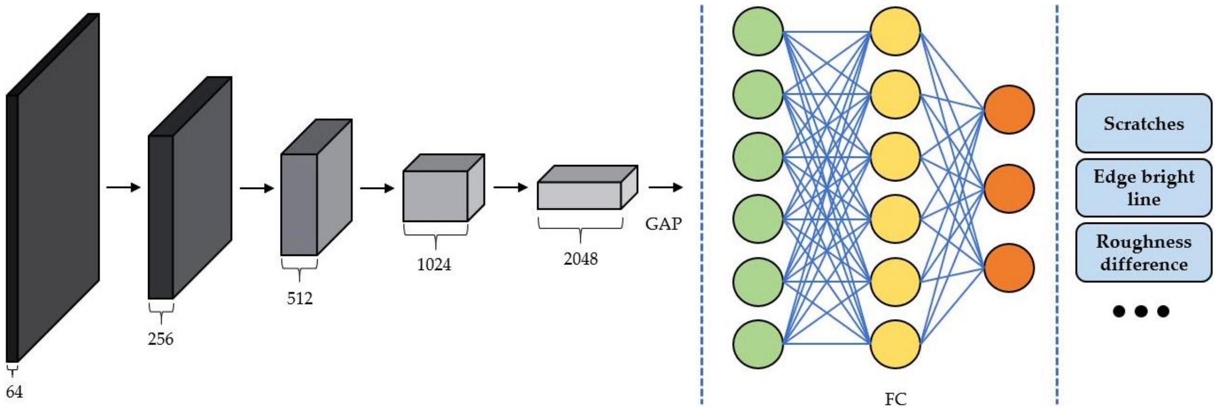


Figure 4: Surface detection system neural network classification and grading model.

4. RESULTS AND DISCUSSION

4.1 Digital simulation of surface quality detection

Based on established surface quality defect setting models and digital simulation studies, defects such as edge bright lines and roughness are analysed. As shown in Fig. 5, the steel plate is first divided into finite element meshes in both length and width directions, followed by digital simulation analysis according to the shape and roughness of the finished strip [24].

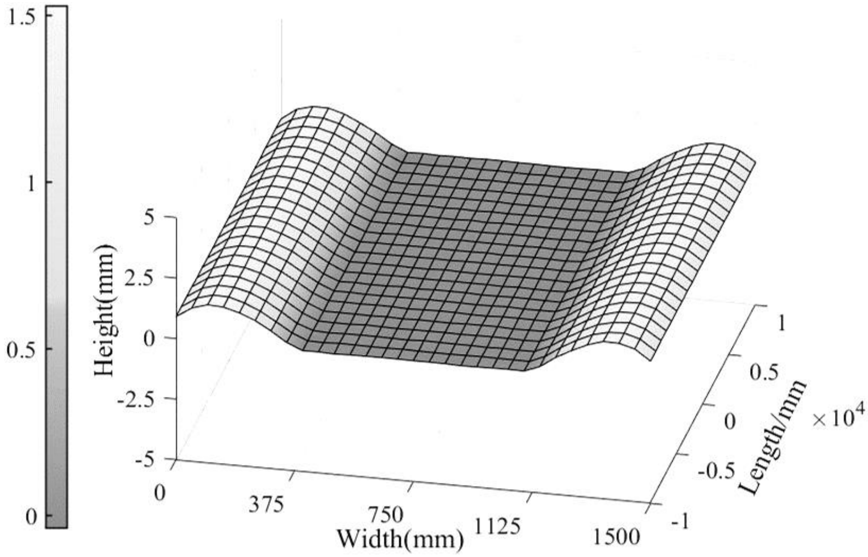


Figure 5: Meshing model.

As shown in Fig. 6, the simulated strip will generate cloud maps distinguished by different colours based on differences in shape or roughness, with the results of the cloud maps being subject to identification analysis and numerical reading. It is evident from Fig. 6 that poor strip edge shape can cause crown issues with a noticeable difference reaching up to 2 mm, resulting in edge bright line defects on the strip.

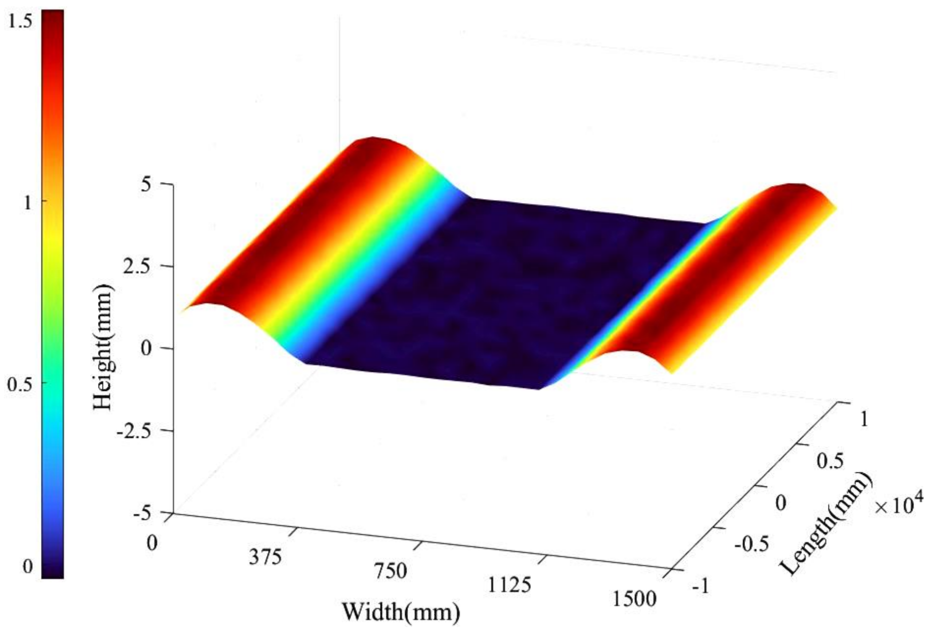


Figure 6: Edge bright line simulation result diagram.

The surface defect setting model analysis was combined with the simulation of scratch defects and roughness colour difference defects on a 10 m long and 1 m wide cold-rolled strip. As depicted in Fig. 7, the scratch simulation revealed the appearance of scratch defects at the end of the strip between 8-9 m, with a distance of approximately 0.3 m between the two scratches. Accurate positioning of the scratch defects is essential for better analysing their root cause. Additionally, as shown in Fig. 8, the simulation for roughness colour difference was conducted. The difference in roughness colour was observed at the beginning of the strip, with a maximum value exceeding 2.8 μm. As the roughness decreases in the rolling direction, it exhibits a steplike distribution and eventually stabilizes below 2 μm. The surface quality setting model simulation is capable of capturing and tracking defects by collecting existing production data, thereby facilitating the preliminary analysis and detection of defects during both preprocessing and post-processing stages of surface quality inspection. This contributes to enhancing system accuracy and control level.

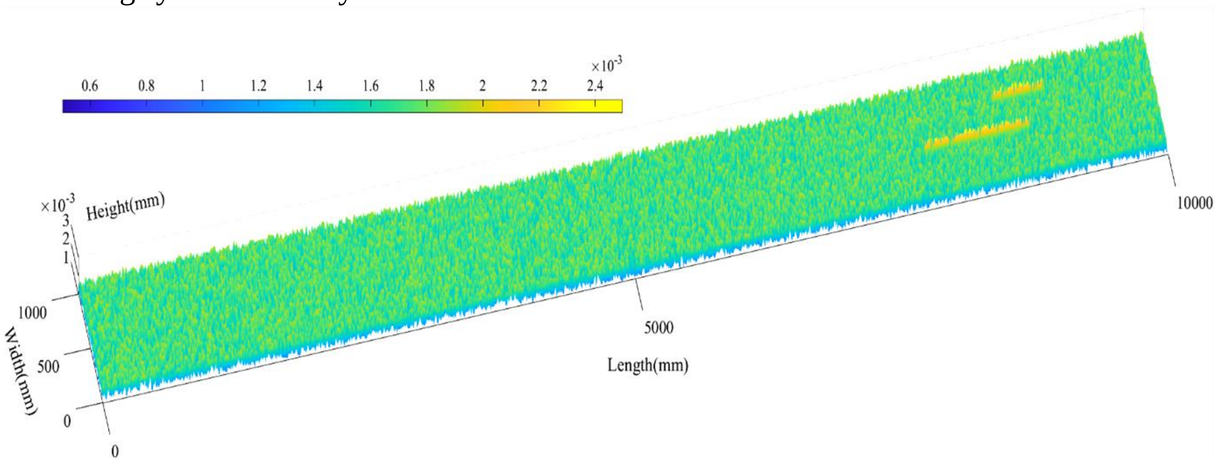


Figure 7: Scratch simulation result diagram.

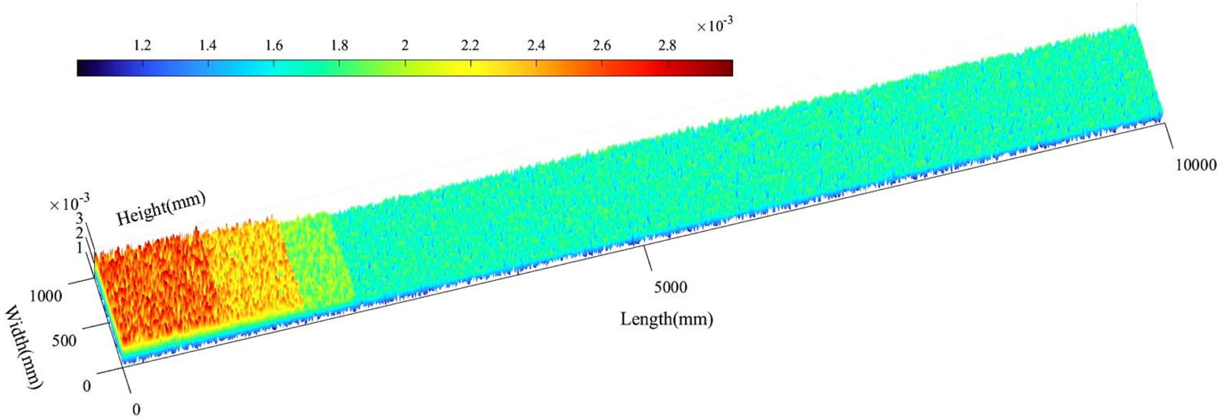


Figure 8: Roughness chromatic aberration simulation result diagram.

4.2 Equipment application of surface quality inspection

In the hot-dip galvanizing production line of manufacturing enterprises, a surface quality inspection system is utilized to capture images of the hot-dip galvanized plates' surfaces for detecting and classifying defects such as scratches, colour differences, and edge brightness lines. Subsequently, the quality map and detection result report are generated for each steel coil, enhancing the existing hot-dip galvanized product quality inspection standards and improving the yield rate. Simultaneously, by correlating defect manifestations with production processes, process personnel are guided to optimize process parameters to reduce or eliminate defects, ultimately achieving the goal of cost reduction and efficiency improvement. Fig. 9 illustrates the comparison of classification effects following application [25].

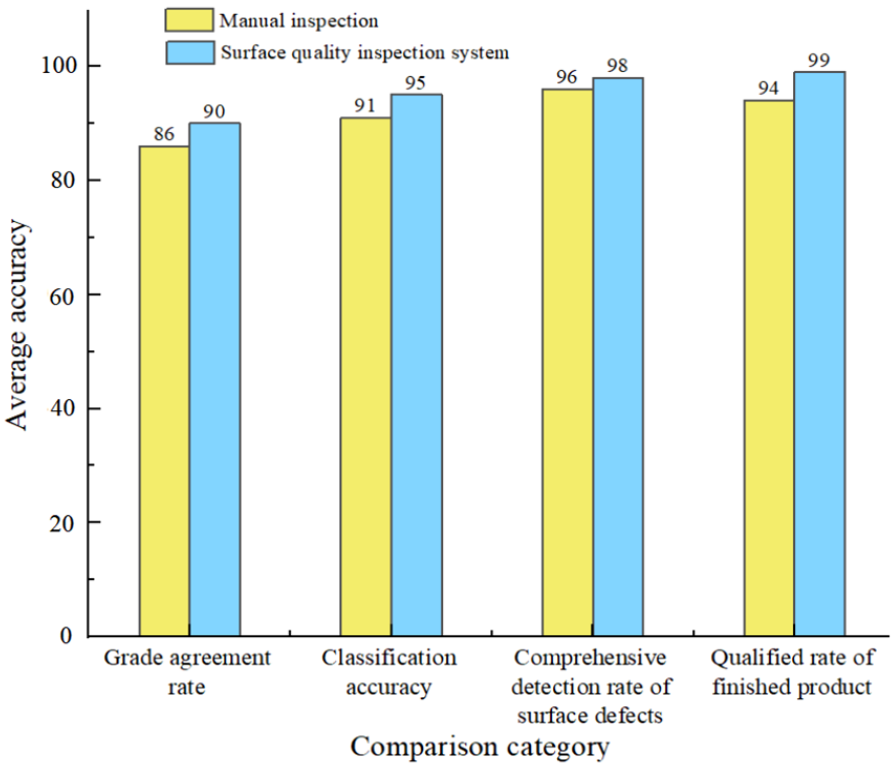


Figure 9: Comparison of application effect classification.

The on-site implementation of surface quality inspection systems and equipment is divided into two distinct stages. In the initial stage, defect detection is accomplished by obtaining defect data through the imaging system, followed by filtering out significant defect images. The primary purpose of collecting these defect images is to alleviate the manual labelling workload. To enhance the efficacy of this first phase, further refinement will be undertaken in terms of application steps. First, resolution design and optical path design are conducted based on sample testing according to the specified requirements. Subsequently, industrial camera light sources and other necessary equipment are deployed on the production line to collect defect data. A model is then constructed using normal images as a basis, followed by the development of an unsupervised self-learning defect algorithm aimed at filtering out images exhibiting significant defects. Finally, we continuously collect image data showcasing significant defects while establishing defect standards and specific defect categories through surface quality defect assessment and model configuration. Furthermore, some images are labelled based on these standards. In the subsequent phase, our focus shifts to locating and classifying defects. Building upon annotated data from the first stage, we train a detection model capable of identifying precise location coordinates as well as specific defect categories. The accumulated dataset is utilized to train an AI model that meets the requirements for both detection and classification capabilities [26].

After the implementation of deep learning-based unit surface defect detection and judgment technology in the hot-dip galvanizing production line, a reduction of 800,000 yuan in labour costs was achieved compared to manual identification. The comprehensive detection rate of surface defects increased from 96 % to 98 %, the accuracy of classification and grading improved from 91 % to 95 %, the consistency rate of automatic grading with manual grading increased from the previous 86 % to 90 %, and the product qualification rate rose from 94 % to 99 %, showing significant effects.

5. CONCLUSION

This study presents a surface defect classification method based on the establishment of a surface quality defect setting model. An unsupervised self-learning algorithm is utilized to identify and classify the surface defects, while strip quality is detected using software and hardware conditions. The data obtained from inspection are simulated and analysed to gain detailed information on defect occurrence for feedback control, resulting in significant advancements of equipment and systems in the field application of surface quality inspection. The main conclusions are obtained as following:

(1) Based on the frequent occurrence of surface quality issues during the production of plate and strip products, specific setting models for scratches, edge bright lines, and plate surface roughness are established to provide channels for surface quality model filtering. These setting models prioritize the order of importance. Through simulation of these setting models, it is possible to accurately reproduce defects using detected data values and obtain detailed morphological information regarding numerical differences in convexity, scratch locations, and roughness values. Additionally, tracking control can be realized for the detection of surface quality defects.

(2) To ensure the widespread application and state-of-the-art nature of this system in the field of strip inspection, a comprehensive surface quality inspection system was established. Improved algorithms for grasping and identification are employed to effectively integrate deep learning results with simulation outcomes. To achieve a better algorithm iteration effect, sample data and AI models are utilized for training, while the accuracy of the algorithm and model is further validated through defect reproduction in model simulations, thereby enhancing defect recognition rates and detection rates.

(3) Through digital simulation and using accumulated data to train the AI model, the detection accuracy is effectively ensured. After on-site application, there was a reduction of 800,000 yuan in labour costs compared to manual identification. The comprehensive detection

rate of surface defects increased from 96 % to 98 %, while the classification and grading accuracy improved from 91 % to 95 %. Furthermore, the automatic grading and manual consistency rate increased from the previous 86 % to 90 %, and the finished product qualification rate also increased from 94 % to 99 %.

This research realizes the efficient combination of modelling, simulation, and application, and fully applies the theoretical model of surface quality defects to the quality inspection system. The next step will be to combine the analysis of massive, measured data to further improve the predictive analysis model.

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