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Computer-Aided Design AND APPLICATIONS

Product Design Defect Detection and Automatic Repair Algorithm Based on CAD and Machine Vision

Zonghua Zhu[1] and Limei Xiong[2]

[1]School of Arts, Jingchu University of Technology, Jingmen, Hubei 448000, China, 199206007@jcut.edu.cn
[2]School of arts, Jingchu University of Technology, Jingmen, Hubei 448000, China, 199306004@jcut.edu.cn

Corresponding author: Limei Xiong, 199306004@jcut.edu.cn

Abstract. Producers need to strictly control the quality of their products when facing customer needs, ensuring the qualification rate of the products. The level of product design is not only related to the abilities of designers themselves, but also the role of design tools in product design cannot be underestimated. This article adopts a defect detection algorithm that combines computer-aided design (CAD) and machine vision and learns and identifies different types of product defects by training deep learning models. This algorithm utilizes the geometric information of products in CAD models and image processing methods in machine vision technology to detect and repair surface defects in product design automatically. The results show that it is significantly superior to the wavelet transform method in terms of detection accuracy, stability, and detail capture ability. Input the product design image to be tested into the model, and the model will output information on the type and severity of defects at each location. By combining deep learning and machine vision technology, this algorithm can more accurately detect and locate various types of product defects.

Keywords: Product Design; Defect Detection; Automatic Repair; CAD; Machine Vision
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1 INTRODUCTION

With the rapid development of industrial technology, people have higher and higher requirements for the quality of products, and due to the limitation of process and mechanical precision, many products will have various defects on their surfaces. The level of product design is not only related to the designer's own ability, but also the role of design tools in product design cannot be underestimated. In today's high-tech manufacturing environment, precise technology and the performance of products. Especially in the production process of printed circuit boards (PCBs), even small defects can lead to the failure of the entire circuit board. Therefore, developing a tool that can accurately and quickly detect these small defects has important value. Ding et al. [1] proposed a new network that performs well in detecting small defects in printed circuit boards. A large number of printed circuit board images and test the TDD network. The experimental results indicate that TDD networks have significant advantages in defect detection and diagnosis. Compared with traditional CNN methods, TDD networks are more accurate and fast in detecting small defects. In addition, by using upsampling layers and bidirectional propagation mechanisms, TDD networks can better identify and locate defects. A large quantity of defects in industrial products are concentrated on the surface of products. Producers need to strictly control the quality of products to ensure the quality of products when facing the needs of customers. During the production process of ceramic products, surface defects may occur due to various reasons, such as cracks, bubbles, and slag dropping. These may affect the strength and safety of the product. Therefore, accurate and efficient detection and repair of surface defects on ceramics. In recent years, machine vision has been widely applied in the detection and repair of ceramic surface defects. Dong et al. [2] explored the application and advantages of repair. Machine vision technology is a technology that utilizes image processing and analysis to detect surface defects on objects automatically. Ceramic surface bubbles are a common defect that affects the aesthetics and strength of products. Machine vision technology can automatically identify bubbles on ceramic surfaces through image processing and analysis and classify and locate them. The surface slagging of ceramics is caused by improper operation. By utilizing machine vision technology, automatic detection of ceramic surface slag can be achieved, enabling timely detection and repair of issues.

In traditional industry, defect detection and quality control are done by experienced employees. However, there is instability in manual testing, and employees are prone to false detection due to subjective and objective factors such as environment and mood, which have a great impact on product quality control. The rise of deep learning technology provides new solutions for surface defect detection. Deep learning technology can automatically learn and recognize the features of surface defects through a large amount of data training, thereby achieving automatic detection of surface defects. This avoids the influence of human factors on the detection results. However, there are still some challenges, such as requirements for detection accuracy, robustness, and real-time performance. To address these issues, Dong et al. [3] proposed a mechanism for automatic detection of surface defects. Through the global contextual attention module, the fused features are further optimized and selected, emphasizing information related to defects and suppressing irrelevant information. Use a classifier to classify and locate the processed features, achieving surface defect detection. The global contextual attention module can capture and utilize global contextual information on the fused features. It optimizes feature representation by calculating the correlation between feature maps, emphasizing features related to defects while suppressing features unrelated to defects. To verify the performance of the PGA network in surface defect detection, we conducted experiments on multiple datasets. Compared to traditional methods, PGA networks improve detection accuracy and robustness while reducing false detection rates. In addition, the PGA network also has good real-time performance. The most important point is that manual testing occupies a lot of human resources and increases production costs, which is completely contrary to manufacturers' basic concept of low cost and high efficiency. At present, manufacturers mainly use industrial automation production lines to produce goods, but because most production lines cannot guarantee a perfect qualified rate, they will inevitably produce defective products that do not meet the technological requirements. However, traditional defect detection methods often require manual involvement and require high skills and experience from inspectors, making it difficult to achieve automation and intelligence. Hu et al. [4] generate a defect distribution likelihood map using the discriminator of DCGAN, where each pixel value represents the probability of defects appearing at that location. By introducing an encoder to the standard DCGAN, the reconstruction of the re-detected image is achieved. When subtracting the reconstructed image from the original image, a residual image can be created to highlight potential defect areas. Combine residual and likelihood maps to form an enhanced fusion map. Using threshold segmentation algorithm on the fusion image to further obtain accurate defect locations. However, traditional CNNs and GANs typically require a large amount of labeled data for training, and their effectiveness is limited when dealing with complex and diverse defect types. The discriminator uses a convolutional neural network structure to undergo adversarial training to achieve unsupervised learning. How to identify and classify defective products efficiently and accurately is a key issue that the industry is paying attention to at present.

CAD has become an important tool in modern product design, greatly improving the efficiency and quality of product design. However, even with advanced CAD tools, various defects may still occur during the product design process. These defects may not only lead to a decrease in product performance but may even cause safety issues. In the production process of steel products, surface defects may occur due to various reasons, such as cracks, pores, inclusions, etc. Therefore, accurate and efficient detection of surface defects on steel is a key step in ensuring product quality. The deep residual neural network is a deep learning model characterized by a deep network structure, which can effectively solve the problem of depth limitation in traditional neural networks. By introducing residual blocks, deep residual neural networks can learn more complex feature representations and achieve better performance in various tasks. For the task of detecting surface defects in steel, we can construct a deep residual neural network ensemble model. This model includes multiple deep residual neural networks, each trained for a specific type of defect. Then, Konovalenko et al. [5] integrated the outputs of multiple networks. It has collected a large number of images of surface defects in steel, including various types of defects such as cracks, pores, inclusions, etc. Then, we trained multiple deep residual neural networks using these images, each targeting a specific defect type. Therefore, how to efficiently and accurately detect and repair these design defects has become a focus of attention in both industry and academia. This article will explore product design defect detection and automatic repair algorithms based on CAD and machine vision in order to provide new ideas for solving this problem. In the past few decades, product quality control has mainly relied on manual inspection and repair, which is not only inefficient but also prone to false positives and missed detections.

Luo et al. [6] explored automatic visual defect detection technology for steel surfaces based on computer-aided design (CAD) and machine vision. Image acquisition is the first step in defect detection, which obtains images of the steel surface through high-resolution cameras and appropriate lighting equipment. The preprocessing steps include denoising, enhancement, and other operations to improve image quality. Feature extraction is a crucial step in extracting feature information related to defects, such as color, texture, shape, etc., through image processing techniques. Finally, the classifier classifies and identifies defects based on the extracted feature information. The experimental results show that this technology can accurately identify and classify various types of defects on the surface of steel and has a high detection speed. Meanwhile, by extracting and utilizing surface features of steel, accurate and efficient defect detection can be achieved. Huang et al. [6] used deep learning and computer vision technology to realize the automatic detection of various types of defects in complex product design. Pan et al. [7] constructed a Convolutional Neural Network (CNN) model using machine vision and deep learning techniques and trained the model using annotated image data to improve its semantic segmentation ability. Use a trained model to perform semantic segmentation on the surface image of a mobile phone screen, separating defective and non-defective areas. Based on the segmentation results, detect and locate the defect area, and output the detection results. Evaluate the detection results and optimize the model based on the evaluation results to improve the accuracy and robustness of the model. Specifically, the 3D model of the mobile phone screen is first established using CAD technology, and then the actual production of the mobile phone screen is imaged using machine vision technology. By extracting features and conducting comparative analysis on the collected images, automatic recognition of defects such as cracks, scratches, and impurities can be achieved. Using image processing techniques to extract features from preprocessed images and extract feature information related to defects. It has a high detection speed and low false detection rate. By combining CAD technology and machine vision, this study realized the automatic and intelligent product design defect detection and repair process to improve production efficiency. This research uses deep learning and computer vision technology to realize automatic detection and repair of product design defects and shows the application prospect of artificial intelligence technology in the industrial field. This is helpful in promoting the development of industrial intelligence and improving the automation level of industrial production. Compared with the traditional research in this field, this article expects to achieve the following innovations:

⊖ Firstly, a product design defect detection and automatic repair algorithm based on CAD and machine vision is proposed to achieve efficient and accurate design defect detection and repair;

⊜ By conducting experiments, we aim to provide an efficient method for product design quality control in the industry;

⊛ By discussing existing technologies and methods, combined with experimental verification and comparative analysis, it is expected to provide useful insights for applications in related fields.

This article aims to explore product design defect detection and automatic repair algorithms based on CAD and machine vision. Firstly, introduce the relevant technical foundations. Finally, the superiority of the algorithm proposed in this article is verified through experiments, and future research directions and application prospects are discussed.

2 RELATED WORK

The deep learning technology has provided new ways to solve this problem. Especially in semi-supervised learning, it can utilize unlabeled data for training, thereby improving the model's generalization ability. Peng et al. [8] proposed semi-supervised learning as a machine learning method that utilizes unlabeled data for training. Semi-supervised learning has been applied to many tasks, such as image classification, object detection, and segmentation. However, there is relatively little research on applying semi-supervised learning to change detection in high-resolution remote sensing images. Recently, some researchers have attempted to combine semi-supervised learning with deep learning to address data imbalance and noise issues in change detection tasks. For example, utilizes unlabeled data to improve the model's generalization ability, thereby improving the performance of change detection. Deep learning has achieved significant success in tasks such as image classification and object detection. Especially convolutional neural networks (CNNs), which effectively combine convolutional and pooling layers, can automatically learn features from images and perform well in the field of image processing. However, in the semiconductor manufacturing field, traditional CNN methods often cannot achieve ideal results in chip defect identification tasks due to the uneven number of different types of defects. In the semiconductor manufacturing process, chip defect identification is a crucial step that has a significant impact on product quality and production efficiency. However, in actual production, due to various factors, there is often an issue of data imbalance. Saqlain et al. [9] proposed a chip defect recognition method based on deep convolutional neural networks (CNN), which is particularly suitable for imbalanced datasets. Compared with traditional CNN methods, this paper has improved both accuracy and recall. In addition, by using data augmentation techniques and attention mechanisms, the method proposed in this paper effectively alleviates the problem of class imbalance and improves the model's generalization ability. Deep learning has made significant progress in the field of defect detection. The accuracy and efficiency of defect detection have been greatly improved. However, for scenarios with multiple complex defect types, such as solar cell manufacturing, existing methods still face some challenges. Solar cell manufacturing is a complex and precise process that involves multiple steps and operations. Due to various factors that may occur during the manufacturing process, solar cells may have various defects, such as scratches, stains, and uneven colors. These defects will seriously affect the performance and lifespan of solar cells. Therefore, it is crucial to detect defects in their manufacturing process. Su et al. [10] proposed a deep learning-based complementary attention network (CAMN) for defect detection in solar cell manufacturing. It trained and tested CAMN on a large-scale dataset of manufacturing defects in solar cells. The experimental results indicate that CAMN has significant advantages in defect detection tasks in solar cell manufacturing. Compared with traditional CNN methods, CAMN is more accurate and comprehensive in detecting multiple complex defect types. In addition, by using attention mechanisms and complementary attention network structures, CAMN can better capture and understand information from different regions of solar cells, improving the accuracy and reliability of defect detection.

Segmentation based deep learning method is a common image processing method, whose basic idea is to segment an image into several regions or objects. In surface defect detection, segmentation-based deep learning methods can segment product surface images into normal and defect regions, making subsequent defect detection and classification convenient. These methods can automatically identify and classify defect types by training and learning a large number of product surface images. During the training process, these models will learn feature information related to defects, such as color, texture, shape, etc. By extracting and utilizing this feature information, accurate and efficient surface defect detection can be achieved. Tabernik et al. [11] Through segmentation-based deep learning methods, product surface images can be segmented into normal areas and defect areas, making it convenient for subsequent defect detection and classification. The experimental results show that this method can accurately identify and classify various surface defects and has a high detection speed. In the wood processing industry, surface defect detection of wood veneers is an important and challenging task. These defects include cracks, color differences, stuttering, burrs, etc., which can affect the quality and appearance of wooden veneers.

Urbonas et al. [12] proposed a method that combines to achieve automatic recognition of surface defects in wood veneers. In order to accelerate model training and improve performance, we adopted the method of transfer learning. We use a pre-trained model on a large amount of image data as the base model and fine-tune it on the surface defect dataset of wood veneer. This enables the model to quickly adapt to new tasks and utilize learned general features for defect detection. The experimental results indicate that our method has significant advantages in detecting surface defects on wood veneers. Compared with traditional defect detection methods, our method has higher accuracy and faster running speed. In addition, through data augmentation and transfer learning, our model can better adapt to different input and defect types, improving generalization ability. Wan et al. [13] extracted features from the segmented defect areas and extracted feature information related to the defects. These features can include texture, color, shape, etc. Based on the extracted feature information, use deep learning models to classify and repair defects. Based on the results of the repair decision, control the automation equipment to perform repair operations on defects. Common methods include polishing, filling, spraying, etc. Use deep learning models to evaluate the quality of the repaired ceramic tile surface, ensuring that the repair effect meets the requirements. Common models include regression models and classification models. Meanwhile, defect repair models based on deep learning can automatically make repair decisions based on defect types and feature information and can achieve high-quality repair of defects. However, the experiment also found some limitations, such as high requirements for data quality and diversity and the need to update and improve the model to improve performance continuously. CAD (Computer Aided Design) technology provides strong support for additive manufacturing. Through CAD software, designers can create and modify 3D models and import them into additive manufacturing equipment. Additive manufacturing equipment stacks materials layer by layer based on CAD model data, ultimately producing products. Additive manufacturing (AM) has become an innovative and highly flexible production method. By combining CAD and machine vision technology, the additive manufacturing cloud platform can achieve fast and efficient product development. Wang et al. [14] explored how to use CAD and machine vision additive manufacturing cloud platforms to accelerate product development. Machine vision technology has brought new opportunities for additive manufacturing. Machine vision systems can automatically recognize, measure, and locate objects, thereby improving the accuracy and efficiency of the production process. Machine vision systems can quickly and accurately identify and locate raw materials, ensuring their correct position and orientation during the manufacturing process. The additive manufacturing cloud platform can achieve rapid prototyping and verification. Designers can send design data to additive manufacturing equipment through cloud platforms to quickly obtain prototype samples. By using machine vision technology for detection and verification, the iteration speed of the product design phase can be accelerated.

Object detection has become an important research direction in the fields of image processing and computer vision. The purpose of object detection is to identify and locate objects in images. For high-resolution visual images, due to their more detailed information and higher resolution, higher performance requirements are put forward for object detection algorithms. Zhang et al. [15]

analyzed the performance of deep learning-based object detection methods in high-resolution visual images. Through the analysis of experimental results, we found that existing objects have some challenges in high-resolution visual images. In order to improve the performance of object detection methods on high-resolution visual images, future research can attempt the following directions: improving the network structure to better adapt to high-resolution images. For example, CNN has been successfully applied to land cover classification tasks sensing images, achieving better classification results than traditional methods. In addition, object detection methods such as YOLO, SSD, etc. are also widely used object detection tasks that can accurately detect target objects in the image. As an important part of beer packaging, the surface quality of beer bottles has a significant impact on the quality of beer and consumer experience. In order to improve the production quality and efficiency of beer bottles and reduce production costs, researchers have attempted to use computer-aided design (CAD) and machine vision technology for defect detection and repair of beer bottles in recent years. Zhao et al. [16] explored how to use CAD and machine vision technology to achieve automatic detection and repair of beer bottle defects. The common types of defects in beer bottles include cracks, bubbles, impurities, etc. These defects not only affect the appearance of beer bottles but, more seriously, may lead to a decrease in the strength of beer bottles and pose safety hazards. Using CAD and machine vision technology for beer bottle defect detection can achieve fast and accurate detection of various defects. Specifically, the 3D model of the beer bottle is first established using CAD technology, and then the actual beer bottle produced is imaged using machine vision technology. By extracting features and conducting comparative analysis on the collected images, automatic recognition of defects such as cracks, bubbles, and impurities can be achieved. In addition, machine learning techniques can also be used to evaluate the quality of repaired beer bottles. By collecting images and extracting features from a large number of repaired beer bottles, a defect detection model can be trained using deep learning algorithms. This model can automatically identify whether the repaired beer bottle has defects and classify the defects. This can effectively improve the quality and efficiency of beer bottle repair.

3 ALGORITHM DESIGN AND IMPLEMENTATION

CAD technology originated in the 1960s and has become an indispensable part of modern engineering design after decades of development. CAD technology improves engineers' efficiency of product design through the powerful computing and graphic processing capabilities of computers. It can create, modify, analyze, and optimize geometric models of product design and provide various tools to achieve operations such as dimension annotation, material selection, and assembly simulation. The CAD technology in this study is mainly used to provide geometric information for product design, including product shape, size, material, etc., providing a foundation for subsequent machine vision processing and defect detection. Computer vision is the science of how to enable computers to obtain information, understand content, and make decisions from images or videos. Computer vision has also been widely applied in multiple fields, including object detection, image segmentation, face recognition, etc. In product design defect detection, computer vision technology is mainly used to extract image information of the product surface and process and analyze this information to detect possible defects.

The deep learning techniques used in this study are mainly used to construct models for product design defect detection and automatic repair. By training deep neural networks to learn how to identify different types of product defects, a more automated product design defect detection and repair process can be achieved. Combining machine vision with deep learning can fully leverage their advantages and achieve more efficient product design defect detection. By utilizing the automatic feature extraction capability of deep learning, more meaningful features can be extracted from images of product surfaces. Meanwhile, by utilizing image processing and analysis techniques of computer vision, the extracted features can be further processed to achieve more efficient defect detection and repair. Because of the complexity and diversity of product design, how to extract effective and robust features is a difficult problem. Traditional feature extraction methods often rely on manual design and selection. The existing algorithms can only deal with a single type of defect, and the effect is not ideal for the coexistence of multiple defects. This article presents an algorithm for product design defect detection and automatic repair based on CAD and machine vision. The algorithm uses the geometric information of products in the CAD model and the image processing method in machine vision technology to detect the surface defects in product design automatically and repair them automatically according to the types and severity of defects. Through the application of this method, it is hoped that the efficiency of product design can be improved, the production cost can be reduced, and a new solution can be provided for the industry.

This section will provide a detailed introduction to how to apply CAD and machine vision methods to product design defect detection and propose a product image recognition and processing model based on deep learning. This model aims to automatically detect surface defects in product design and automatically repair them based on the type and severity of the defects. The product design defect detection and automatic repair algorithm includes the following steps:

(1) Data preprocessing: Preprocessing CAD models and machine vision images, including format conversion, size normalization, noise removal, and other operations.

(2) Feature extraction: Utilize geometric information from CAD models and image processing methods in machine vision technology to extract key features in product design.

(3) Defect detection: Based on the proposed product image recognition method, analyze the extracted features to detect possible types and locations of defects.

(4) Automatic repair: Based on the detected defect type and severity, use image processing methods in machine vision technology to automatically repair defects.

(5) Result evaluation: Evaluate the repaired product to improve the repair effect further.

Figure 1 shows three lighting methods: backlit,forward-lit, and coaxial-lit. Backlit method: Place the light source below the object being measured, and this lighting method can capture the edge contours of the object being measured very clearly. In general, in black-and-white images, the measured object appears black with a white background, which can form a distinct black-and-white contrast and is easy for image software to process. Forward lighting method: In contrast to the backlighting method, the light source is placed on the same side of the object being measured and the camera. In practical applications, this lighting method is mostly used. This lighting method can be divided into high-angle illumination and low-angle illumination according to the difference in the angle between the light source and the surface of the object being measured. Coaxial light method: Refers to placing the light source between the object being measured and the camera.

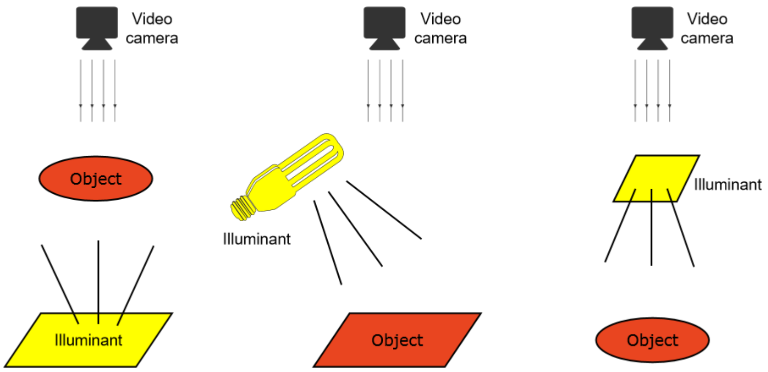

Figure 1: Three lighting methods.

Due to the possibility of different formats in CAD models, it is needed to convert them to a unified format for subsequent defect detection processing and analysis. This article converts CAD models to STL format. This format is a universal 3D model format that can be supported by most CAD software.

In order to process images of different sizes uniformly, it is needed to normalize the image size to the same size. This study uses the bilinear interpolation method to normalize the size of images to ensure their clarity and detailed information. Due to the possibility of noise and interference in the images obtained by machine vision, such as uneven lighting, shadows, reflections, etc., it is needed to perform noise removal operations on them. Extract key geometric features of product design, including shape, size, angle, etc., using geometric information from CAD models. Using image processing methods in computer vision technology, extract key image features of product design, including surface texture, color distribution, edge contours, etc.

Design a suitable Convolutional Neural Network (CNN) model for product defect detection. The model should include multiple convolutional layers, pooling layers, and fully connected layers to extract useful features from the input image and classify them. Applying the trained CNN model to actual product design defect detection. Input the product design image to be tested into the model, and the model will output information on the type and severity of defects at each location. Based on this information, complete automatic repair or prompt the operator to manually repair. As shown in Figure 2, CNN is a feedforward neural network constructed by mimicking biological vision mechanisms with sparse connectivity characteristics. Ability to learn lattice features, such as pixels and audio, with minimal computational complexity. Numerous experiments have shown that the characteristics of CNN in extracting image features are capturing image textures at the bottom layer and preserving image content at the top layer.

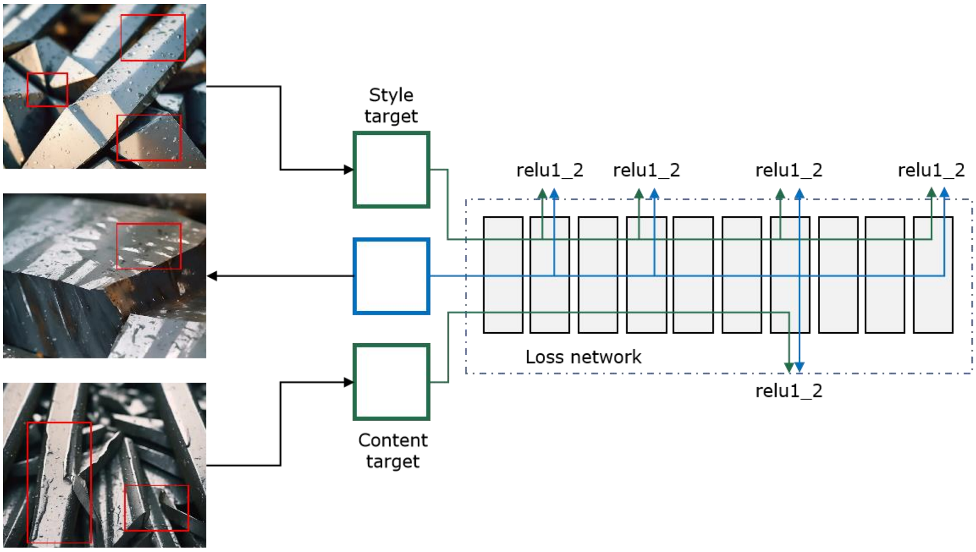

Figure 2: Algorithm model in this article.

$$J(\theta) = \frac{1}{N}\sum_{i=1}^{N}\left\| y^{i} - h\left(x^{i};\theta\right)\right\|^{2} \tag{1}$$

Where N is the quantity of samples. For linear regression problems, $h(x)$ is a linear function, so $J(\theta)$ is a convex function. Minimizing $J(\theta)$ can directly obtain the optimal solution by numerical method; For neural networks, $h(\theta)$ is a complex nonlinear function, and it is impossible to get the optimal solution directly. Therefore, the parameters θ in the network should be updated by gradient descent to find the local optimal solution. The most commonly used objective function in classification tasks is the cross entropy loss function. Cross entropy can be used to represent the error between the distribution of Softmax function output and the empirical distribution.

The most commonly used objective function in classification tasks is the cross entropy loss function. Cross entropy can be used to represent the error between the distribution of Softmax function output and the empirical distribution. Assume that the real tag corresponding to the i th sample x^{i} is y^{i}, and $y^{i} \in 1,\ldots,K$, that is, a total of K classes are output. The cross-entropy loss function is:

$$J\ \theta\ = -\left[\sum_{i=1}^{N}\sum_{k=1}^{K} 1\ y^{i}\ = k\ \log\frac{\exp\left(\theta_k x^{i}\right)}{\sum_{j=1}^{K}\exp\left(\theta_j x^{i}\right)}\right] \tag{2}$$

Where $\theta = \ \theta_1,\theta_2,\ldots,\theta_K$ is the parameter in the network output by using the Softmax function, and N is the number of samples. $1\ \cdot$ is an indicator function.

Train and optimize deep learning models using annotated datasets to learn and identify different types of defects automatically. In order to improve the training effectiveness and convergence speed of the model, techniques such as batch normalization and regularization are used to improve the model. The model will output defect type and severity information for each location for subsequent defect repair. Let A and B be two sets on Z, and B be the structural element to inflate B, and the inflation result is recorded as:

$$A \oplus B = \ z \middle|\ B'\ _z \cap A \neq \varnothing \tag{3}$$

Where B' is the origin reflection of B about itself. The expansion result is composed of displacement elements Z and B' has at least one element overlapping with A in terms of displacement of these elements. Generally, the expansion operation is used to connect adjacent parts in an image. B is used as a structural element to corrode A, and the corrosion result is recorded as:

$$A \Theta B = \ z \middle|\ B_z\ \subseteq A \tag{4}$$

Contrary to the dilation operation, the erosion operation is mostly used to disconnect the adjacent parts in the image and filter the excessively fine parts, such as isolated points. B As a structural element to open and close A is defined as:

$$A \circ B = \ A \oplus B\ \Theta B \tag{5}$$

$$A \cdot B = \ A \Theta B\ \oplus B \tag{6}$$

Open operation and close operation can filter out the connection between small discrete points and discrete areas of the image while keeping the image shape basically unchanged.

In the experiment of using the sparsity of coefficients for defect detection of different products, the selection of basis functions is crucial. These basis functions are obtained through training and are used to represent different types of product defects. Figure 3 shows the image of defective product samples used to train the basis function. These images contain product defects of different types and severity. By training and learning from these images, a set of basis functions can be obtained to represent different product defects.

$$\nabla f\ x,y\ = \left[G_x, G_y\right]^T = \left[\frac{\partial f}{\partial x}\frac{\partial f}{\partial y}\right]^T \tag{7}$$

Figure 3: Sample images of defective products used for training basis functions.

Where G_x and G_y are gradients along the direction x and y, respectively, and the amplitude $\left|\nabla f(x,y)\right|$ and direction angle of the gradient are:

$$\left|\nabla f(x,y)\right| = \left(G_x^2 + G_y^2\right)^{1/2} \tag{8}$$

$$\phi(x,y) = \arctan\left(\frac{G_y}{G_x}\right) \tag{9}$$

For digital images, the amplitude $\left|\nabla f(x,y)\right|$ of the gradient of the above formula can be replaced by differential and used as the value of each pixel of the formed image:

$$\left|\nabla f(x,y)\right| = \left\{\left[f(x,y) - f(x+1,y)\right]^2 + f(x,y) - \left[f(x,y+1)\right]^2\right\}1/2 \tag{10}$$

4 EXPERIMENTAL VERIFICATION AND RESULT ANALYSIS

4.1 Result Analysis

The start recording button creates two shooting objects simultaneously and performs independent shooting in two different threads. This multi-threaded processing mechanism enables two cameras to work in parallel, improving shooting efficiency and processing speed. By shooting in different threads, potential thread conflicts and resource contention are avoided, ensuring the stability of the shooting. After pressing the start recording button, the display module will be called and the images captured by the two cameras will be displayed in real-time. By observing the real-time displayed images, operators can promptly detect defects on the surface of the product and take corresponding measures. Figure 4 shows the running interface of the product defect detection software.

On the production line, any delay can lead to a large quantity of defective products being produced. Therefore, the software needs to issue a warning at the moment of detecting a defect. When the product surface defect detection software detects surface defects, its interface will quickly respond, issue a warning, and enlarge the defect area, as shown in Figure 5. The appearance of warning messages and the enlargement of defect areas are both aimed at enabling operators to have a more intuitive understanding of the current problem. By analyzing historical warning data, common problems, trends, or potential causes on the production line can be identified, providing decision-making support for management. The recall results of the comparison algorithm for product surface defect detection are shown in Figure 6. From the graph, it can be seen that the algorithm proposed in this article performs well in terms of recall, with an improvement of over 20% compared to traditional wavelet transform algorithms.

Figure 4: Detection software running interface.

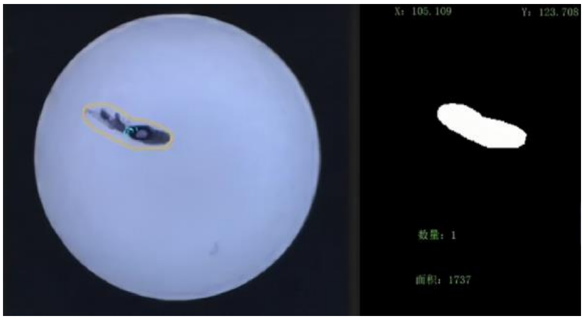

Figure 5: Warning interface of product surface inspection software.

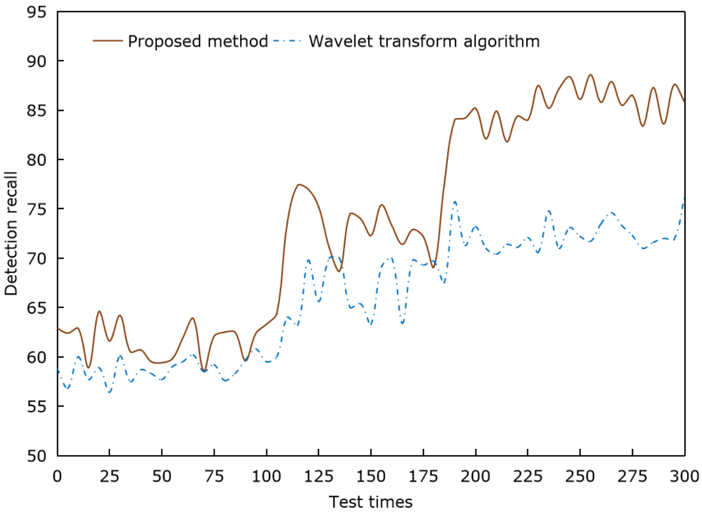

Figure 6: Comparison of recall of product surface defect detection.

By combining CAD models and machine vision technology, richer product information can be obtained, including precise geometric shapes, surface textures, etc. Through extensive training and optimization, deep learning models can capture finer and more complex defect features, thereby improving the recall of detection. The algorithm in this article can accurately locate the edge contours of product surface defects. This is due to the powerful feature extraction and classification capabilities of deep learning models, as well as the sharp capture of detailed information by sparse encoding methods.

Figure 7 shows the simulation results using wavelet transform. Some points are relatively far from the straight line, which means that in some cases, there is a significant deviation between the detection results and the actual results. Figure 8 shows the results of using the algorithm proposed in this article, where the points are more tightly clustered near the straight line. This indicates that the output results of the algorithm in this article are closer to the actual results. By comparing Figures 7 and 8, the simulation results of using the algorithm proposed in this article for product defect detection can be visually observed.

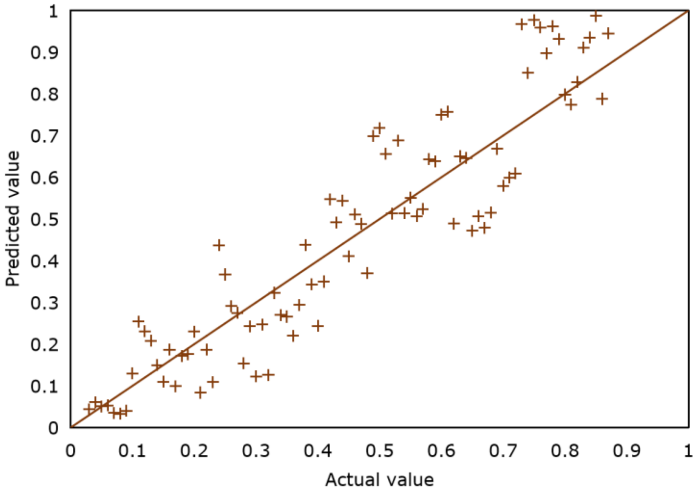

Figure 7: Test results of wavelet transform.

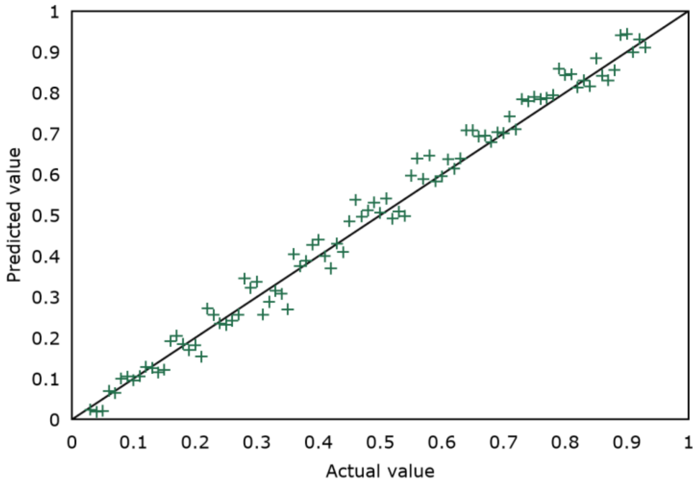

Figure 8: Test results of this algorithm.

Wavelet transform exhibits instability in handling certain complex and nonlinear product defects. This may be due to the limitations of wavelet transform in processing high-frequency noise or abrupt signals. The algorithm presented in this article clearly demonstrates higher stability in handling these complex situations. This is attributed to the deep learning techniques or other advanced signal processing methods used in the algorithm, which enable it to better capture and identify various types of product defects.

4.2 Discussion of Results

By comparing the recall of product surface defect detection algorithms, it was found that this algorithm has an accuracy higher than the comparison algorithm by more than 20%. When surface defects are detected on the product, the product surface defect detection software interface can quickly issue a warning and enlarge the defect area, allowing operators to intuitively understand the detailed situation of the defect. This interface design improves the operator's perception of defects, and the enlarged defect area also provides convenience for repair work.

By comparing the simulation results of using wavelet transform and our algorithm for product defect detection, it is found that our algorithm is superior to the wavelet transform method in terms of accuracy and efficiency. By applying sparse encoding methods and deep learning techniques, various defects on the surface of products can be detected and located more accurately. This provides valuable feedback information for the product design phase, helping designers identify and correct design issues in a timely manner. Through the warning and amplification functions of the product surface defect detection software interface, operators can quickly perceive and understand the defect situation on the product surface, and take corresponding repair measures in a timely manner.

The application of these methods and technologies provides strong support and guidance for product design, quality control, and production process improvement, helping to improve product quality, reduce production costs, and enhance enterprise competitiveness.

5 CONCLUSION

A large quantity of industrial product defects are concentrated on the surface of the product, so surface defect detection plays a crucial role in ensuring product quality. In the past few decades, product quality control has mainly relied on manual inspection and repair, which is not only inefficient but also prone to false positives and missed detections. In this article, an algorithm for product design defect detection and automatic repair based on CAD and machine vision is proposed to realize efficient and accurate design defect detection and repair. By comparing and analyzing the effectiveness of wavelet transform and our algorithm in product defect detection, we clearly demonstrate the significant advantages of our algorithm in terms of detection accuracy, stability, and detail capture ability. This algorithm has successfully constructed an efficient and accurate product defect detection system, which can timely detect and accurately locate various types of product defects. Through the warning and amplification functions of the product surface defect detection software interface, operators can quickly perceive and understand the defect situation on the product surface, and take corresponding repair measures in a timely manner.

The adaptability of algorithms is an important research direction for product defects of different types and production environments. Future research can focus on developing more intelligent and adaptive algorithms that can automatically learn and adjust to adapt to changes in various scenarios, thereby improving the generalization ability of algorithms. Through continuous innovation, it is expected to provide more intelligent product defect detection solutions for the manufacturing industry, driving it toward a high-quality direction.

Zonghua Zhu, https://orcid.org/0009-0005-7920-1992
Limei Xiong, https://orcid.org/0009-0000-6482-6774

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