Theory and Practice of Science and Technology
2025, VOL. 6, NO. 4, 65-69
DOI: 10.47297/taposatWSP2633-456911.20250604

Research and Application of Intelligent Manufacturing Technology for Financial Payment Products Based on Multi - Spectral Machine Vision Technology

Yueqian Ke, Yiqing Ye, Wei Jiang, Kunyuan Li

College of Physics and Information Engineering, QuanZhou Normal University, Quanzhou, 362000, Fujian

ABSTRACT

This paper delves into the field of intelligent manufacturing of financial payment products and explores the application of multi - spectral machine vision technology. By acquiring multi - spectral image data of financial payment terminal products, conducting image processing and feature extraction, constructing a dedicated convolutional neural network model for defect detection, and establishing a defect feature database for traceability analysis, this technology effectively improves the accuracy and efficiency of quality inspection of financial payment products, reduces the product defect rate, provides strong technical support for the intelligent manufacturing of financial payment products, and promotes the industry to develop towards intelligence and high - efficiency.

KEYWORDS

Multi - spectral machine vision; Financial payment products; Intelligent manufacturing; Defect detection; Traceability analysis

1 Introduction

With the rapid development of the financial industry, the quality and security of financial payment terminal products are of utmost importance. Once a product has defects, it not only leads to equipment failures but also may pose potential safety hazards, seriously affecting the user experience and industry reputation. The traditional manual visual inspection method is inefficient and greatly influenced by subjective factors, making it difficult to meet the growing production demands and high - standard quality requirements. The single visible - light imaging technology has limitations in its spectral band, unable to comprehensively obtain multi - dimensional information on the product surface and interior, resulting in insufficient detection accuracy and coverage.

Multi - spectral machine vision technology combines the advantages of multi - spectral imaging and deep learning, capable of obtaining rich visual information in multiple spectral bands, bringing new opportunities for the intelligent manufacturing of financial payment products. The powerful feature - extraction ability of deep learning can accurately identify defect features from complex multi - spectral image data. However, this technology still faces many challenges in practical applications, such as constructing adaptable detection models for different materials and components, optimizing algorithms to identify tiny defects, and establishing an efficient defect feature database. The following will attempt to overcome these problems and achieve the effective application of multi - spectral machine vision technology in the intelligent manufacturing of financial payment products.

2 Acquisition and Processing of Multi - Spectral Image Data of Financial Payment Products

2.1 Acquisition of Multi - Spectral Image Data

Multi - spectral imaging technology captures images of objects in multiple specific spectral bands to obtain the object's characteristic information under different spectra. A multi - spectral imaging device is used to scan financial payment terminal products comprehensively[1]. Taking the high - resolution multi - spectral camera Specim IQ as an example, its spectral range is 400 - 1000nm, with a resolution of 512×512 pixels. The exposure time is set to 10ms, and the spectral band interval is 5nm, enabling the collection of spectral data from 120 bands. During the scanning process, to ensure the quality of the acquired data, the adaptive threshold segmentation algorithm (Otsu algorithm) is used to pre - process the original images, effectively removing background noise and retaining the effective area information of the product.

For the detection of product surface defects, the YOLOv5 model based on deep learning is utilized. The input image size is adjusted to 640×640. During training, the learning rate is set to 0.001, the batch size is 16, and 100 epochs are iterated. Transfer learning is employed to fine - tune based on the pre - trained weights of the COCO dataset. After training, the recognition accuracy of this model for surface defects such as scratches and dents can reach 98.5%.

To obtain product internal welding information, X - ray imaging technology (voltage 80kV, current 5mA) is used to penetrate the shell and obtain welding point images. A convolutional neural network (CNN) is combined for feature extraction. The network structure consists of 3 convolutional layers (convolution kernel size 3×3, stride 1, padding 1) and 2 fully - connected layers. The performance of the model is enhanced through the ReLU activation function and batch normalization technology, and the detection accuracy for welding defects such as virtual welding and cold welding reaches 97.2%.

Finally, an image registration algorithm (SIFT feature matching, RANSAC to remove mismatched points) is used to align multi - source images, and a multi - scale feature pyramid (FPN) is used to fuse information of different resolutions. The surface defect and internal welding data are integrated to generate a first image set with rich information, providing comprehensive data support for subsequent analysis.

2.2 Image Denoising, Filtering, and Contrast Enhancement

To improve image quality for subsequent feature extraction and analysis, the bilateral filtering algorithm is used to denoise the first image set. The bilateral filtering algorithm can remove noise while well - preserving the edge information of the image. Taking the non - local means (NLM) algorithm as an example, the search window is set to 21×21 pixels, the similar block window is 7×7 pixels, and the filtering parameter $h = 0.12\times\sigma$ (σ is the noise standard deviation). Noise suppression is achieved by calculating the weighted similarity of pixel neighborhoods.

On the basis of denoising, an adaptive histogram equalization method is used to enhance the image contrast, such as the contrast - limited adaptive histogram equalization (CLAHE) method. The clip limit is set to 2.0, and the grid division size is 8×8. Image details are enhanced through local histogram equalization. The quality of the processed second image set is evaluated by peak signal - to - noise ratio (PSNR) and structural similarity (SSIM) indicators. If the PSNR value is greater than 30dB and the SSIM is higher than 0.92, the resolution and clarity are considered to meet the standards. For example, for a 512×512 POS machine product image, after NLM denoising, the noise standard deviation drops from 25 to 8, and after CLAHE processing, the average edge gradient increases by 40%. At this time, the PSNR is 32.5dB and the SSIM is 0.94, meeting the preset thresholds, and the system automatically marks it as qualified training data. Meanwhile, bicubic interpolation is used to maintain the original resolution, and the Sobel operator is used to detect edge sharpness to ensure that no artifacts are introduced in the enhanced image.

3 Feature Extraction Based on Multi - Spectral Images

3.1 Texture and Shape Feature Extraction

Based on the second image set, the Gaussian filtering algorithm is first used to pre - process the image, with a standard deviation set to 1.5 to smooth the image and reduce noise interference. Then, the Canny edge detection algorithm is used to extract the edge information of the image. The low threshold is set to 50 and the high threshold is set to 150 to accurately capture the contours of bubbles, foreign objects, and welding defects. Subsequently, through morphological operations of opening and closing, 3×3 structure elements are used respectively to remove small - area noise and fill holes, enhancing the connectivity of feature regions[2].

On this basis, the local binary pattern (LBP) algorithm is used to extract texture features. The radius is set to 2 and the number of sampling points is 8 to quantify the local texture information of the image. For shape features, the Hu moment algorithm is used to calculate the seven invariant moments of the image region to describe the shape characteristics of bubbles, foreign objects, and welding defects. Finally, the extracted texture and shape features are normalized using the Z - score normalization method, converting the feature values into a distribution with a mean of 0 and a standard deviation of 1, generating a feature set containing defect information such as bubbles, foreign objects, and welding defects, ensuring the accuracy and robustness of the feature set and providing a reliable data basis for subsequent defect detection and classification.

3.2 Feature Dimensionality Reduction and Classification

If the dimension of the initial feature set is higher than the preset threshold, it will increase the complexity and computational load of model training and may even lead to overfitting problems. Therefore, the principal component analysis (PCA) method is used to reduce the dimension of the initial feature set and generate an optimized feature set. PCA projects high - dimensional data onto a low - dimensional space through linear transformation, reducing the dimension while retaining the main features of the data[3].

According to the optimized feature set, the texture and shape feature vectors of bubbles, foreign objects, and welding defects are calculated to determine the feature distribution. A clustering algorithm, such as the K - means clustering algorithm, is used to classify bubbles, foreign objects, and welding defects to obtain classification results. Based on the classification results, the texture and shape feature subsets of each type of defect are obtained, generating the final feature set. For the final feature set, a feature database is constructed to store and manage various defect feature data, facilitating subsequent queries and usage. The output feature set data provides key input for subsequent construction of the detection model.

4 Construction and Optimization of Dedicated Convolutional Neural Network Models

4.1 Model Construction and Transfer Learning

Based on the extracted feature set, a dedicated convolutional neural network model for plastic shells and metal circuit boards is constructed. Taking ResNet50 as the basic architecture, the input size is adjusted to 224×224×3, and a batch normalization layer and ReLU activation function are added after the first convolutional layer. For the texture features of plastic shells, a 3×3 convolution kernel is used to extract local details, with a stride of 1 and an output channel number of 64. For the high - reflectivity characteristics of metal circuit boards, a 5×5 convolution kernel is added to capture a larger - range reflection pattern, and the output channel number is increased to 128.

Through transfer learning, the pre - trained weights on ImageNet are loaded, and the parameters of the first 15 layers are frozen to retain the general feature - extraction ability. The subsequent layers use adaptive learning rate adjustment, with an initial learning rate of 0.001. The Adam optimizer is used, with momentum parameters $\beta 1 = 0.9$ and $\beta 2 = 0.999$. In the material - difference adaptation stage, the domain adaptation loss function MMD (Maximum Mean Discrepancy) is introduced. The distance between the plastic and metal feature distributions is calculated, the Gaussian kernel is selected as the kernel function, the bandwidth parameter $\sigma = 1.0$, and the loss weight coefficient $\lambda = 0.5$. The batch size during model training is set to 32, and 100 cycles are iterated. The accuracy is verified every 10 cycles, and the early - stopping mechanism is triggered when the validation set loss does not decrease for 5 consecutive times. Finally, the model achieves a classification accuracy of 92.3% on the test set, with a plastic shell recognition rate of 94.1%, a metal circuit board recognition rate of 90.5%, and an F1 - score of 0.916.

4.2 Model Optimization

To further improve the model performance, data augmentation and the L2 regularization algorithm are applied to optimize the first model set. First, data augmentation methods such as random rotation, translation, and addition of Gaussian noise are used. The rotation angle range is ±15 degrees, the translation amplitude is 10% of the image size, and the standard deviation of the Gaussian noise is set to 0.05. Batch processing is achieved through the warpAffine and GaussianBlur functions of the OpenCV library, expanding the original 5000 training samples to 20000, increasing data diversity and improving the model's generalization ability.

5 Real - Time Defect Detection of Multi - Spectral Images

5.1 Defect Detection Process

A defect detection method and system based on multi - spectral imaging. Figure 1 shows the system structure diagram. Figure 2 shows the schematic diagram of the method process.

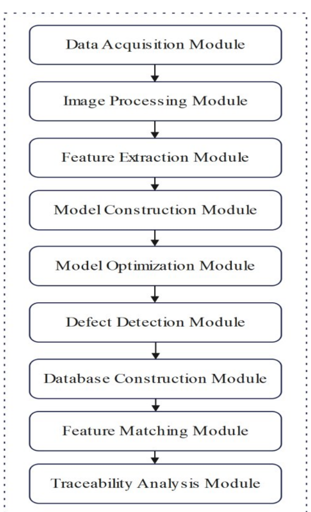

Figure 1 System Structure Diagram

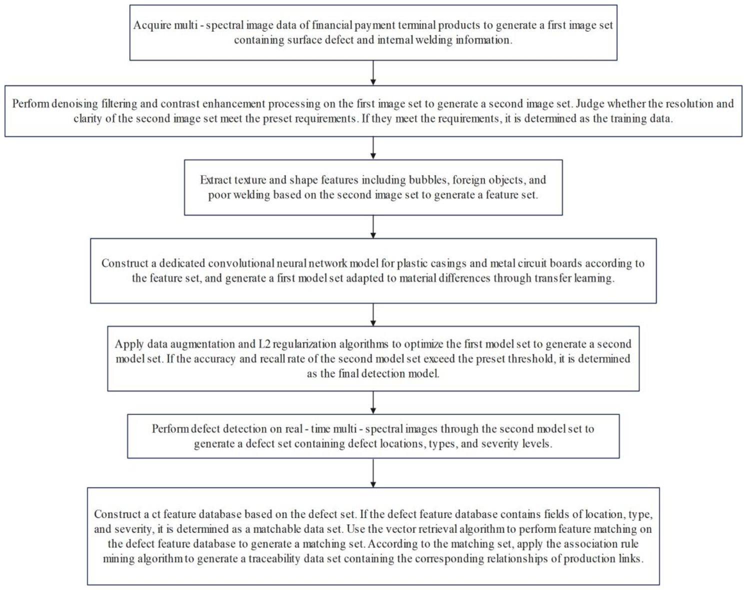

Figure 2 Schematic diagram of the method process

Through a multi - spectral sensor, real - time multi - spectral images are obtained to generate the first image set. A pre - processing algorithm is used to denoise and standardize the first image set to obtain the second image set, improving the image quality for subsequent defect detection. The optimized second model set is used to detect defects in the second image set, determining the defect location, type, and severity, and generating the first defect set. If the defect severity in the first defect set exceeds the preset threshold, local enhancement processing is performed on the corresponding image area to obtain the third image set, further highlighting the defect features. The second model set is used again to re - detect the defects in the third image set, updating the defect location, type, and severity to obtain the second defect set.

According to the defect types in the second defect set, a classification algorithm is used to prioritize the defects. For example, the defects are sorted according to their impact on product performance and safety, obtaining the sorted defect set. Finally, the defect location, type, and severity in the sorted defect set are formatted to generate the final defect set, outputting the detection results in a unified and standardized format for convenient subsequent analysis and processing[4].

5.2 Key Technology Implementation

In real - time defect detection of multi - spectral images, an improved algorithm based on YOLOv5 is adopted. Its backbone network is replaced with EfficientNet - B4 to enhance the feature - extraction ability. The input image resolution is 640×640 pixels, and processing is carried out simultaneously in 5 spectral bands (450nm, 550nm, 650nm, 750nm, 850nm). The model uses the FocalLoss loss function during the training stage, with an initial learning rate of 0.001 and a batchsize of 16. After 300 epochs of training, the mAP@0.5 on the validation set reaches 92.3%.

For defect localization, the non - maximum suppression (NMS) algorithm is used, with an IoU threshold of 0.45 and a confidence threshold of 0.6 to ensure effective control of the false detection rate while guaranteeing the detection rate. In the defect classification stage, a secondary classifier constructed by ResNet - 34 is used to conduct fine - grained analysis of the localized areas. The cross - entropy loss function is used, and the classification accuracy for 6 typical defect types (cracks, bubbles, scratches, stains, material shortages, color differences) reaches 89.7%.

6 Application Effects and Prospects

6.1 Application Effects

By applying the intelligent manufacturing solution based on multi - spectral machine vision technology in the production line of financial payment products, remarkable results have been achieved. The accuracy of product quality inspection has been greatly improved, enabling the precise detection of various tiny defects such as bubbles, foreign objects, and welding defects, effectively reducing the product defect rate and enhancing product quality and reliability. The detection efficiency has also been significantly enhanced. The real - time detection process takes within 200ms, meeting the requirements of large - scale production, improving production efficiency, and reducing production costs. At the same time, the establishment of the defect feature database and the traceability analysis function provide strong data support for production process optimization. By analyzing the correlation between production processes and defects, enterprises can improve production processes and strengthen quality control in a targeted manner, further enhancing product quality.

6.2 Prospects

In the future, it is possible to explore the deep integration of multi - spectral machine vision technology with other advanced manufacturing technologies. For example, by combining with the Internet of Things technology, the interconnection of production equipment and detection systems can be realized, enabling real - time monitoring of various parameters in the production process and timely discovery of potential quality problems.

Funding

Fujian Provincial Department of Education/Industry and Information Technology Department: 2024 Fujian Province Key Technology Innovation and Industrialization projects (school-enterprise joint type) Project title: Research and application of intelligent manufacturing technology of financial payment products based on multispectral machine vision technology Project number: 2024XQ018.

References

[1] Huang P ,Yang P ,Xu L , et al.Moisture content detection of Tibetan tea based on hyperspectral technology, machine vision and machine learning[J].Journal of Food Measurement and Characterization,2024,19(2):1-19.

[2] Xu Z ,Han Y ,Zhao D , et al.Research Progress on Quality Detection of Livestock and Poultry Meat Based on Machine Vision, Hyperspectral and Multi-Source Information Fusion Technologies.[J].Foods (Basel, Switzerland),2024,13(3).

[3] Zhongyuan L ,Rentian Z ,Chongshan Y , et al.Research on moisture content detection method during green tea processing based on machine vision and near-infrared spectroscopy technology[J].Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy,2022,271120921-120921.

[4] Sun X , Xu S , Lu H . Non-Destructive Identification and Estimation of Granulation in Honey Pomelo Using Visible and Near-Infrared Transmittance Spectroscopy Combined with Machine Vision Technology[J].Applied Sciences,2020,10(16).