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Detecting Defects With Support Vector Machine in Logistics Packaging Boxes for Edge Computing

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ABSTRACT The accuracy of defects detection for logistics packaging box is a critical factor to ensure the quality of goods under edge computing environment. Now, there are few works on this issue. This paper designs an image acquisition process system and then proposes a novel approach in addressing logistics packaging box defect detection (LPDD) on the basis of support vector machine (SVM). Firstly, this paper designs a new mean denoising template and Laplace sharpening template, which are more suitable for logistics packaging based on image preprocessing, image enhancement and other relevant technical theories. Then in the stage of noise removal, this paper proposes an improved morphological method and a gray morphological edge detection algorithm. The edge defect detection of a gray image is carried out by combining the above two methods. Hence, LPDD extracts the features of logistics packaging box by using scale-invariant feature transform (SIFT) algorithm and designs SVM classifiers to classify the logistics package defects. This paper uses a large number of samples to train, learn and test the designed SVM classifier. The simulation results show that the proposed LPDD method can accurately detect two common types of defects in logistics packaging boxes with higher accuracy and less computational costs, which meets the requirements of manufacturers on the classification and recognition of defects in machine vision detection system.

INDEX TERMS Package defects, logistics packaging box, support vector machine (SVM).

I. INTRODUCTION

Logistics is playing an irreplaceable role as a bridge for e-commerce development. Packaging plays an important role in logistics and transportation. The standard logistics packaging box not only facilitate logistics transportation but also protect the commodities. The damage of the logistics packaging box will directly affect the quality of the goods. Therefore, it is significant to detect the defects of logistics packaging box timely.

The manual detection method is the traditional way of defecting detection and is characterized by low sampling rate, accuracy, and efficiency, poor real-time performance, high labor intensity, and sensitivity to artificial experience. Then, aiming at such limitations, there is an urgent need to the intelligent data detection and processing technologies which can be applied in the edge computing filed, while considering the requirement of improving the performance of smart data analysis in edge computing.

In recent years, the software and hardware technologies of computer vision system have been promoted rapidly with the development of electronic technology. High resolution and speed camera and image acquisition system are widely used in the process of logistics, which meet the requirements of defects detection for logistics packaging box based on image processing [1]–[3].

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The machine vision-based defect detection system includes the following modules: image acquisition, image processing, and image analysis. The image acquisition module mainly consists of charge coupled device (CCD) cameras, optical lenses, and light sources. The image processing module mainly involves image denoising, image enhancement and restoration, defect detection, and object segmentation. The image analysis module is mainly concerned with feature extraction, feature selection, and image recognition.

Specifically, the machine vision-based detection methods can significantly overcome these disadvantages by manual detection. Tang et al has summarized the experience and statistics of a large number of defect detection cases based on machine vision [4]. Then, artificial neural networks and support vector machines (SVMs) are the most widely used statistical pattern recognition methods. Fang et al adopted a defect detection algorithm framework consisting of a fast speeded-up robust features (SURF) extraction algorithm, a bag of words (BoW) algorithm, and a one-class SVM for drug packaging [5]. Qiu et al proposed a highly efficient deep learning-based method for pixel-wise surface defect segmentation algorithm in machine vision [6]. He et al proposed a new method based on convolutional autoencoder (CAE) and semi-supervised generative adversarial networks (GANs) for surface defect classification of steels [7]. Although these detection methods based on machine vision present many achievements and applications in surface defect detection of metal, paper printing, textile, ceramic tile, glass, and wood, there are few works on defect detection in logistics packaging boxes. Moreover, the existing achievements mainly focus on surface defect detection, but do not consider the combination of surface defect and edge defect.

Considering cartons are most widely used in logistics, this paper focuses on the defects detection in the carton box. Generally, by analyzing the defects package box, the defects of the logistics packaging box are divided into the following five categories.

(1) Lost-label. The logistics label is not properly gummed down and comes off the package box.
(2) Deformation. The deformation of logistics packing box is made by the force and repeated extrusion.
(3) Crack. The carton seams crack and the joint width does not meet the package requirements.
(4) Surface damage. The cartons have surface damages, such as holes, cracks, and many others.
(5) Surface dirty. The carton's surface is smudged, and dirty objects attach to logistics packaging box.

Among the above five types of defects, it is easy to detect the first defect, and such defect on carton does not affect the quality of internal goods. The last four defects are difficult to detect by image processing and could cause damage to the internal goods. Therefore, this paper mainly focuses on the image detection of the last four defects. According to the different features of logistics packaging defects, the defects detection in logistics box can be divided into two categories. The first type of defect is logistics package edge defects, in which the edge width of the package box is larger or smaller than the standard one. The other type of defects is logistics package surface defects, in which the brightness of defects area is different from other normal areas [8]–[10].

In this paper, we focus on two kinds of defects, and design an image acquisition process system, while proposing a novel approach in logistics packaging box defect detection (LPDD) by using SVM. Considering the computational complexity and the cost of time, this paper uses SVM to realize defect recognition instead of convolutional neural network (CNN) after the previous experiments. Here, LPDD includes image preprocessing, defect feature extraction, SVM classification, and other processes.

The main contributions of this paper are summarized as follows.

(1) This paper develops an image acquisition process system which can detect logistics packaging box defects, and then proposes a novel approach in addressing LPDD based on SVM. The proposed LPDD can detect two kinds of logistics packaging box defects efficiently.
(2) Based on image preprocessing, image enhancement and other relevant technical theories, we design a new mean denoising template and Laplace sharpening template, which are more suitable for logistics packaging.
(3) In the stage of noise removal, we propose an improved morphological method and a gray morphological edge detection algorithm. The edge defect detection of a gray image is carried out by combining the above two methods. It can achieve the intelligent processing and analysis of data in edge computing [11].
(4) The proposed defect detection system can effectively improve the detection accuracy, improve the detection efficiency, and reduce the detection cost. In addition, the research results of this paper can be used in the automatic sorting of logistics to provide a real-time judgment of packaging defects for automatic sorting, which is of great significance to improve the transportation quality of goods.

This paper includes six sections. Our image acquisition and process system is described in Section II. Section III describes the detail preprocessing procedure of LPDD, which includes image grayscale, image binarization, image denoising, and improved morphological process. Section IV designs the SVM-based defects detection of logistics packaging box. This paper analyzes the proposed approach through an exhaustive systematic performance study and simulations in Section V. Finally, this paper is concluded in Section VI.

II. THE IMAGE ACQUISITION AND PROCESS SYSTEM FOR LOGISTICS PACKAGING BOXES

Because there are different manufacturers in the market, the logistics packages are also diverse [12]–[14]. This paper focuses on the most common logistics packaging boxes. Figure 1 shows the appearance of logistics packaging boxes.

FIGURE 1. Front view of logistics packaging boxes.

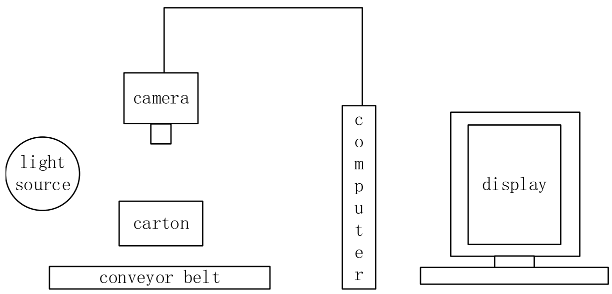


FIGURE 2. Hardware system for the visual acquisition of package defects.

As shown in Figure 2, our visual acquisition system of logistics packaging boxes includes lots of hardware, such as light source, computer, image acquisition card, and camera. The automatic sorting of logistics can use our visual acquisition system as internet of things (IoT) devices in edge computing field [15], [16].

To achieve the shooting of the carton boxes, the camera needs to have a certain environmental contrast, which requires a light source to provide ideal lighting. If the system is without the light source, the follow-up work may be quite complicated.

In the process of determining the actual light source, the following problems need to be analyzed: coverage area, lighting indicators, power consumption. Current luminescent solutions focus on the following: sodium lamp, halogen lamp, light bulb, mercury-vapor lamp, and LED lamp. Among them, fluorescent lamps, halogen lamps, and LED lamps are the common light sources in machine vision lighting. Color yellow halogen lamp, fluorescent lamp of the green color, so in the process of system design, choice of LED lights, implements the basic test requirements, the effect of light source is to provide support for related acquisition module lighting, not only can effectively solve the effect of outside light, and the feature parameters of image is more significant, facilitate subsequent processing and analysis. The light

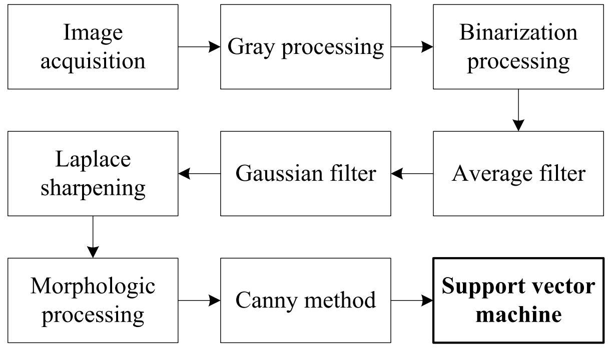


FIGURE 3. Flow chart of the logistics packaging image detection algorithm.

source can provide the required illumination for the acquisition module of the system. On the one hand, it can avoid the negative effects of the surrounding environment; on the other hand, it can highlight the features of the image, facilitating the subsequent processing and analysis process.

As for the camera, we apply TXG12 gigabit industrial camera from PMG company to acquire the image of the carton. The image is transmitted over the gigabit network to the industrial computer. Moreover, it costs 20 ms to acquire and transmit one frame of an image, which meets the requirements of speed. Light source and camera constitute the image acquisition module. Industrial computers, Programmable Logic Controller (PLC) and other components of the conveyor belt motion control and image processing system can achieve the automated inspection of logistics package boxes. The execution control system of defective goods elimination realizes high speed and high accuracy elimination of defective logistics packing boxes.

III. THE PREPROCESSING FOR LOGISTICS PACKAGING IMAGE

Due to the influence of logistics labels, uneven boxes' body, and other factors, there may be some noises in the acquired package image, and it will bring negative effects to detect and classify package defects in logistics package carton boxes. Therefore, it is necessary to preprocess the package image to highlight the defect feature of logistics package boxes and reduce the noises, which can improve the accuracy and speed of the defect detection and classification algorithm of logistics packaging boxes. Figure 3 shows the image detection algorithm flow of logistics packaging boxes.

A. IMAGE GRAYSCALE

Logistics packaging boxes are generally colored. So the digital images of logistics packaging boxes have usually the color information in RGB color space. In this way, a color image will be three times the size of pixel information in terms of storage space. Grayscale implementation can reduce the storage space of image information and speed up image processing. After the implementation of grayscale, the image storage space reduces to 1/3 of the original one. From the perspective of mathematical models, grayscale processing can be divided into linear grayscale processing and nonlinear grayscale processing [13].

This paper selects the linearized grayscale processing, and it is as follows:

$$f = \omega_1 R + \omega_2 G + \omega_3 B \tag{1}$$

where ω_1, ω_2, and ω_3 represent the proportion of R, G and B in the image space, respectively. In our system, when the value of ω_1, ω_2, and ω_3 is (0.299, 0.587, 0.114), the contrast effect of the grayscale process is the most similar to the original color image.

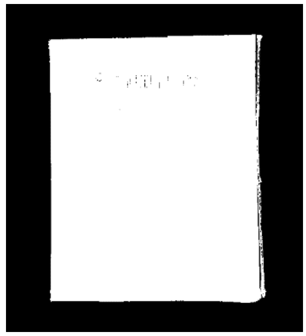
B. IMAGE BINARIZATION

If there is no distinct difference between the packaging area and the background area in the image of logistics packaging boxes, it will be difficult for subsequent segmentation and detection. In light of that, it is essential to improve the contrast between the packaging area and the background area.

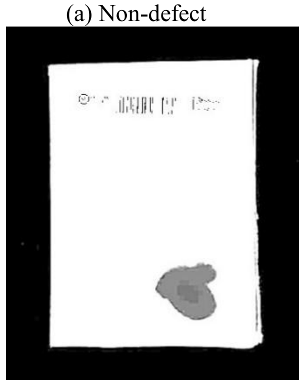
Extracting the packaging area and defecting feature area is the key to work in this paper. The threshold methods are common methods for the region segmentation. Because the gray information of the image is often significant differences between the target and the background, a threshold value can be set to distinguish the target from the background [17], [18].

Binarization is a classic method of thresholding. After binarization, the pixels are matched with pure black or pure white information respectively. And the contrast effect is more obvious.

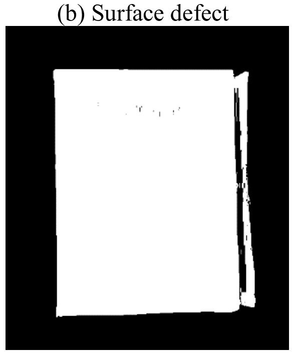
Based on the mathematical principle and implementation process of OTSU algorithm, the calculation of reasonable threshold value depends on the calculation of an inter-class variance. Generally, the variance of different images has great fluctuation. Besides, the larger inter-class variance denotes a more significant difference between the target and the background. After processing color conversion with OTSU, the storage space of the packaging image reduces to a third of the original one, which also lays a foundation for further binarization processing. The binarization processing can further highlight the differences between foreground and background areas, which facilitates the detection of packaging feature areas and defects. After binarization processing, the image of the logistics packaging boxes is shown in Figure 4.



(a) Non-defect



(b) Surface defect



(c) Edge defect

FIGURE 4. Logistics packaging boxes processing image after binarization.

Figure 4(a) shows the processing result of non-defect logistics packaging boxes. Figure 4 (b) shows the result of logistics packaging boxes with surface defects. Figure (c) is the result of the logistics packaging boxes with edge defects. As shown in Figure 4, there is much residual noise that will interfere with the recognition of defects. So what follows is image denoising.

C. IMAGE DENOISING

During the process of shooting, images will be affected by different kinds of noise. Random noise accounts for the largest proportion of all noises. The influence of noise on the image information has two ways. The first one is the additive relation between noise information and image information. The second way is the multiplicate relation between noise information and image information.

The de-noising process in this paper includes three steps. Firstly, random noise is processed. Secondly, Gaussian noise is processed. Lastly, the ambiguity that may be caused by the first two steps is presented clearly. In this paper, the noise of the logistics packaging image is removed according to the following steps.

Step 1: Generally, the logistics packaging surface has many kinds of materials, such as order tags, tapes, and other complex situations. Hence, the removal of random noise has a great influence on subsequent defects detection. If random noise can not be handled properly, the result of defects detection may be wrong. Through a lot of experimental exploration, we design new mean denoising templates for surface defect detection in logistics packaging boxes, which includes

2.25	2.25	2.25
2.25	2.25	2.25
2.25	2.25	2.25

1	1	1
1	0	1
1	1	1

FIGURE 5. Flow chart of the logistics packaging image detection algorithm.

-1	-1	-1
-1	9	-1
-1	-1	-1

FIGURE 6. Self-designed convolution kernel.

two templates of 9 pixels. The mean denoising templates are shown in Figure 5.

The first template is to perform the lookup function, which is to find the location of the noises. During each search, the searched pixel is put in the middle of the template. Then the average value of all the pixels in the template is calculated. The calculation principle is as follows:

$$\hat{f}(x, y) = \frac{1}{9} \sum\nolimits_{0 \le x, y \le 2} f(x, y) \tag{2}$$

where $(x,\ y)$ denotes the position of the pixels. The average information of all pixels in the entire template can be obtained, and the comparison of pixel information at the location can be performed and found. If the difference between the two pixels exceeds the preset range, we consider that the pixel is polluted by noise. If the difference between the two pixels is not beyond a preset range, the pixel point is not noise. After that, the following denoising of the second template is performed.

$$f_1(1, 1) = \frac{1}{8} \left(\sum\nolimits_{0 \le x, y \le 2} f(x, y) - f(1, 1) \right) \tag{3}$$

Step 2: For logistics packaging boxes, Gaussian noise mainly affects small damage defects. It is more convenient to remove such noise because Gaussian noise satisfies the statistical law of Gaussian distribution. The Gaussian filter can be directly used to remove it as follows:

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{1}{2\sigma^2} \left(x^2 + y^2 \right) \right) \tag{4}$$

where $G(x, y, \sigma)$ denotes a symmetric function, σ is the tuning control parameter.

Step 3: Laplace sharpening is used to sharpen image information after the above two filters. Mean filtering removes random noise in the image, and Gaussian filtering removes Gaussian noise in the image. But any filter methods will lead to the blurring of the image details. To facilitate the subsequent process, the self-designed convolution kernel is adopted to perform Laplace sharpening and remove the previous fuzzy effect. The self-designed convolution kernel is shown in Figure 6.

1	0	0	1
0	1	1	0
0	1	1	0
1	0	0	1

(a) x-shaped structure

1	0	0	0
0	1	0	0
0	0	1	0
0	0	0	1

(b) linear structure

FIGURE 7. Two structural elements.

D. AN IMPROVED MORPHOLOGICAL PROCESS

The minor defects in logistics packaging boxes are reflected in some small points and areas. Then, the morphological process is appropriate for the enhancement of these features.

The morphological process is a kind of mathematical theory. When it is applied in the field of image process, the main forms are corrosion operation, expansion operation, open operation, and close operation. The operation of morphological segmentation for minor defects in logistics packaging boxes is the combination of the above four functions as follows.

$$F = [f \Theta F_{G1}] \Theta [f \Theta F_{G1}] \tag{5}$$

Aiming at the limitation of the traditional morphological algorithm of a single structure element, this paper proposes an improved morphological edge detection algorithm based on the features of the gray-scale logistics packaging image. The improved algorithm uses multiple structural elements to detect the defect edge of the gray-scale image. The improved algorithm can overcome the insensitivity to image edges with different directions and significantly improve the edge detection effect [19]. This paper adopts the following two structural elements, namely x-shaped structure, and linear structure, as shown in Figure 7.

Given the pre-processed gray-scale image of logistics packaging boxes is f', morphological gradient operation is carried out respectively according to the above structural element B_i $(1 \le i \le 2)$. The morphological gradient is obtained as follows.

$$g_i(f') = (f' \oplus B_i) - (f' \Theta B_i) \tag{6}$$

$$\begin{aligned} f'' &= \sum\nolimits_{i=1}^{2} \omega_i g_i(f') \\ &= \sum\nolimits_{i=1}^{2} \omega_i [(f' \oplus B_i) - (f' \Theta B_i)] \end{aligned} \tag{7}$$

where ω_i is the weight of edge detection of different structural elements B_i, $0 \le \omega_i \le 1$.

Figure 8 illustrates the comparison results after the morphological process. Figure 8(a) is the schematic diagram of defect extraction after the traditional single structure element morphological algorithm processing. Figure 8(b) is the schematic diagram of defect extraction by using the improved morphological process. As shown in Figure 8, the improved morphological process proposed is more conducive to the subsequent identification of defects in the logistics packaging boxes.

(a) (b)

FIGURE 8. **Comparison diagram of experimental results.**

E. MARKING DEFECT AREAS WITH EDGE DETECTION METHOD

Canny operator is a multi-stage optimization operator with filtering, enhancement, and detection, which can achieve a good balance between noise suppression and edge detection. The basic idea is as follows. It firstly selects a certain Gaussian filter to smooth the image, and then uses non-extremum suppression technology to process the smoothed image to get the final edge image. The key to edge detection is to select appropriate Gaussian filter domain size and appropriate threshold. The noise suppression effect can be better by increasing the filter field size [20].

The first step is to convert the image to grayscale, which can reduce the storage space. The second step is image binarization to segment the background. The third step is image denosing to remove noise interference with defects. The fourth step is to process the noise of small defects by the improved morphology algorithm. Finally, we can tick out edge images with Canny algorithm. Through the above steps, we can get a clear target image, and then realize feature extraction and classification recognition in the next step.

The minor defects in logistics packaging boxes are reflected in some small points and areas.

IV. SVM-BASED DEFECTS DETECTION OF LOGISTICS PACKAGING BOXES

Feature extraction and classifier design are the most important parts of the whole process. Scale invariant feature transform (SIFT) is a local feature descriptor proposed by David Lowe, which has been developed rapidly and used widely. Because SIFT feature points are extracted by extremum detection in scale space, they have translation and scale invariance. At the same time, each feature point has the main direction, so the rotation invariance is maintained within a certain range. Finally, the extracted feature vectors have good illumination invariance by normalization. Therefore, this paper selects SITF to extract feature vectors, e.g., rotation angle and brightness of logistics packaging boxes, which are classification basis of SVM classifier [21], [22].

SVM classification algorithm focuses on three parts: data extraction, function selection, and training classifier. The steps of the learning algorithm based on SVM are as follows:

Step 1: collect data and extract feature points through SIFT algorithm.

Step 2: obtain visual words and select the kernel function with high accuracy.

Step 3: train the classifier and test the accuracy of the classifier.

This paper uses large amounts of packaging samples to extract the edge and surface eigenvectors, which form the input data of the SVM classification. Then, the SVM classifier is trained and recognition is carried out. With the popular use of machine learning algorithms in many fields [23]–[31], SVM as a supervised learning method has been widely used in the statistical classification and regression analysis [32]–[34].

For input data with linear inseparability, the SVM classification completes the calculation in low-dimensional space firstly, and then maps the input space to the middle of high-dimensional features through kernel function, and finally constructs the optimal separation hyperplane in high-dimensional space, to avoid the complex calculation in high-dimensional space. The case that becomes linearly separable in this space is actually converted to solve the following optimization problem:

$$\begin{aligned} &\min \left\{ \frac{1}{2}\|w\|^2 + C\sum\nolimits_{i=1}^{n}\xi_i \right\} \\ &\text{s.t. } y_i(w^{\mathrm{T}}x_i + b) \geq 1-\xi_i, \quad i=1,\cdots,n;\ \xi_i \geq 0 \end{aligned} \tag{8}$$

where w is the weight vector and b is the offset. Given the training sample (x_i, y_i) $(i = 1, \ldots, n)$, Lagrangian operator is used to find the maximum objective function:

$$\begin{aligned} &Q_\alpha = \sum\nolimits_{i=1}^{n}\alpha_i - \frac{1}{2}\sum\nolimits_{i,j=1}^{n}\alpha_i\alpha_j y_i y_j \langle x_i, x_j\rangle \\ &\text{s.t. } 0 \leq \alpha_i \leq C; \quad i=1,\cdots,n; \ \sum\nolimits_{i=1}^{n}\alpha_i y_i = 0 \end{aligned} \tag{9}$$

This paper designs a SVM classifier based on the number of input eigenvectors, the number of output classification types, the selection of kernel function types, and multi-category classification methods. The samples are divided into three types: lossless package, edge defect and surface defect, according to eigenvectors of lossless package, edge defect and surface defect images. Therefore, the number of input eigenvectors is 3, and the number of output classification types is 3. According to this classification method, the classification order is non-defect, edge defect and surface defect. The classification flow chart is shown in Figure 9.

The common kernel functions of SVM include polynomial, radial basis function (RBF), Sigmoid, and some others. Among them, RBF achieves better classification performance in practical engineering. Through the comparison tests, we select the radial basis kernel function as the kernel function of SVM as shown in the following equation.

$$K(X, X) = \exp\left(-\frac{1}{2\sigma^2}\|x - x_i\|^2\right) \tag{10}$$

where σ is a control parameter. The radial basis kernel function is extremely flexible and used widely. Figure 10 shows the performance comparison of three kernel functions.

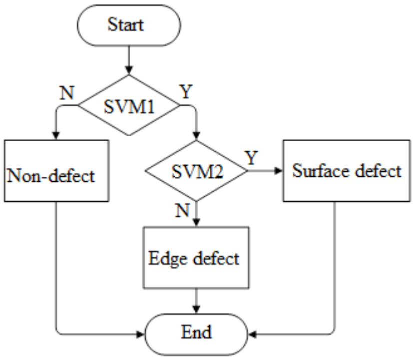


FIGURE 9. The flow chart of classification.

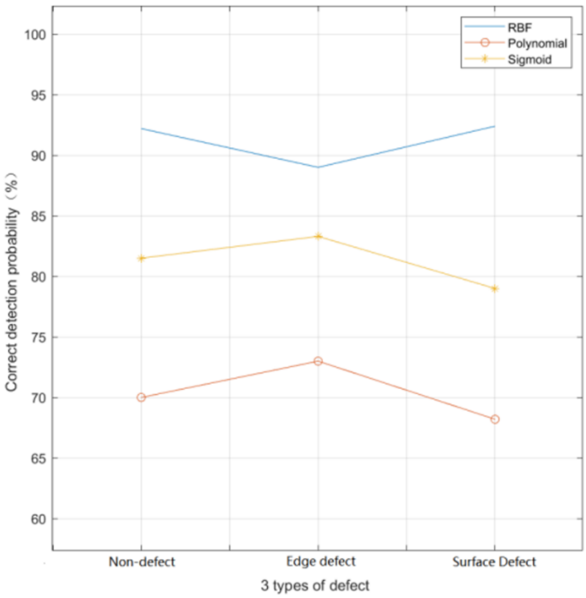


FIGURE 10. Performance comparison of three kernel functions.

V. EXPERIMENTAL RESULTS AND ANALYSIS

In our experiments, we acquire 300 original samples for each defect, and process and expand them to 3000 samples. Then, 3000 samples are used for experiments. Here, 2100 samples are randomly selected for training, and the remaining 900 samples are used for testing. Besides, 2000 samples without defects are also selected, in which 1100 samples are randomly selected for training, and the remaining 900 samples are used for testing. Hence, the training set has 6300 samples, and the test set has 2700 samples.

The experiments are conducted on the following computing environment: TXG12 gigabit camera, Inter Core i5 4200CPU, annular LED light source and surface light source. And the image acquisition process system for defect detection can be applied in the actual logistics scenario shown in Figure 11.

The software system is developed in Window10 system based on python. Moreover, the calculation of feature vectors and the training and testing of the classifier are all

FIGURE 11. Actual logistics scenario.

TABLE 1. Logistics packaging boxes defects classification test results.

	Number of Sample	Number of successful detection	Correct detection probability/(%)
Non-defect	900	820	92.20
Surface defect	900	830	92.40
Edge defect	900	810	89.00
Total	2700	2460	91.20

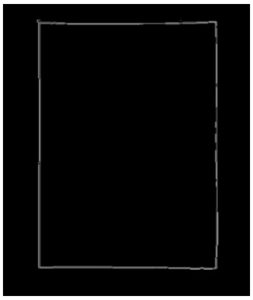
implemented by Open CV library function. The resolution of the image is 500×653.

Figure 12 shows the classification and detection results of defects in logistics packaging boxes. Figure 12(a) is the process result of logistics packaging boxes without damage. Figure 12(b) and Figure 12(c) are the process result of surface defects of logistics packaging boxes. Figure 12(d) and Figure 12(e) are the process results of edge defects of logistics packaging boxes.

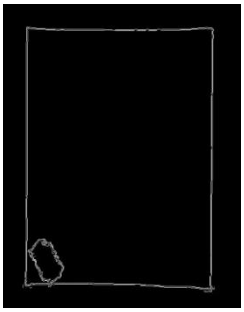
The eigenvectors of each sample image in the training set are calculated, and 6300 groups of eigenvectors are extracted and added to the SVM classifier for classification training. The error threshold to stop training is set to 0.001. After the training of the SVM classifier, we use the remaining 2700 samples to test the SVM classifier. Table 1 shows the classification and detection results of defects in logistics packaging boxes.

As shown in Table 1, the classification and recognition rate of the SVM classifier designed in this paper can reach 91%, which can meet the requirements of high precision in the production process. Among the three defects, the classification effect of surface defects is the best, and the classification effect of edge defects is poor since the image features of edge defects are relatively close to non-destructive features.

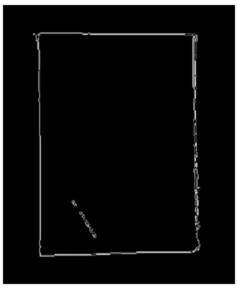
The proposed approach is based on small original samples. Compared with some other deep learning algorithms, SVM can detect defects quickly and in real-time. In the early stage, we use a deep learning algorithm, i.e., CNN, to detect defects. The experimental results show the detection rate of non-defect and surface defect is 66%, and the detection rate of



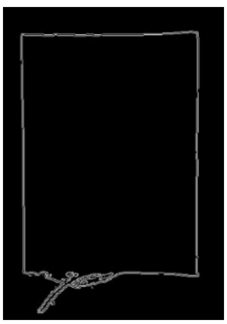
(a) Non-defect



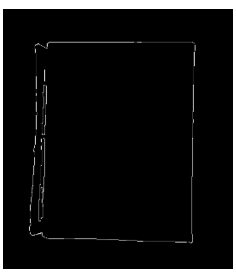
(b) Surface defect



(c) Surface defect



(d) Edge defect



(e) Edge defect

FIGURE 12. Classification results of defects in logistics packing boxes.

edge defects is 40%. However, the detection time is many times of that of the proposed approach in this paper.

VI. CONCLUSION

Considering that there are few works on defects detection in logistics packaging boxes for the application of intelligent processing and analysis of data in edge computing, this paper designs an image acquisition process system and proposes a novel approach in LPDD based on SVM. Firstly, the original package image is preprocessed by graying and binarization. The package image is denoised according to the features of package defects. Then, the improved multi-scale and multi-structure elements are designed to enhance the small and medium defects in the image. Meanwhile, the improved morphological process makes the extraction of the image contour effectively. LPDD extracts the features of logistics packaging boxes by using the SIFT algorithm and designs SVM classifiers to classify the logistics package defect. This paper uses 3000 samples to train and test the designed SVM classifier. The experimental results show that the proposed LPDD can accurately detect two common types of defects in logistics packaging boxes with higher accuracy and fewer system costs, which meets the requirements of manufacturers on the classification and recognition of defects in the vision detection system.

The results also indicate that the selection of feature attributes and the quality of training samples directly determines the training and testing effect of the classifier. In order to achieve a better classification effect, it is necessary to conduct an in-depth study on the features of various logistics packaging boxes defects and to select the features that can better distinguish all kinds of defects.

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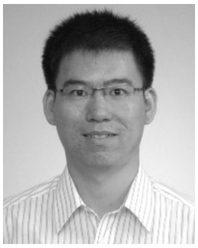

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