Multi-operator feature enhancement methods for industrial defect detection

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Abstract. Deep learning based object detection algorithms have been gradually applied to industrial defect detection, but the resulted accuracy does not fully meet the needs of industrial inspection. In order to enhance image features, this paper proposes a series of image preprocessing schemes based on edge detection operators, using a single-operator preprocessing scheme, a multi-operator serial preprocessing scheme and a multi-operator parallel preprocessing scheme for image preprocessing of data to enhance the edge features of images. The validation experiment of the SSD based object detection algorithm is performed on dataset used for industrial inspection, to verify the effectiveness of the processing schemes above. The result shows that the multi-operator based image preprocessing method is effective in improving the accuracy of surface defect detection in the field of industrial defect detection.

1. Introduction
Automatic detection of surface defects is a very important aspect of the product quality in the automated production of industrial products, and it is widely used in chip surface inspection, fabric surface inspection, steel surface inspection, wood and tile surface inspection, etc\textsuperscript{[1]}. It has been found that deep learning has powerful feature extraction capabilities, and the supervised object detection methods based on deep learning approach have shown accuracy and robustness that are difficult to achieve with traditional detection methods. More and more companies are trying to use deep learning based object detection algorithms as a solution for surface defect detection, but industrial production has more stringent standards for defect detection, whereas the current defect detection algorithms are not fully up to standard.

2. Research Status
The results of the supervised deep learning object detection are mainly determined by two parts, the object detection algorithm itself and the training dataset. In practice, if the dataset has problems such as unbalanced distribution of species or the presence of noise, it can lead to a decrease in detection accuracy\textsuperscript{[2-3]}, so the data is usually enhanced before the model is trained to improve the defect detection accuracy.
Current image enhancement methods in the field of object detection are divided into three main
categories: traditional single-image processing algorithms, multi-image fusion algorithms, and deep
learning adversarial generation algorithms. Single-image processing methods mainly include
texture enhancement, color enhancement, and blurring; geometric enhancement performs
operations such as flipping, panning, cropping, deformation and scaling on images; color
enhancement includes brightness variation, Color Jittering, PCA Jittering, 3DLUT, etc; blurring
enhancement entails using various filtering schemes for image processing, commonly used are median
filtering, Gaussian filtering, bilateral filtering, etc. Multi-image fusion
algorithm is generally a cut and stitch, overlay and other operations on 2-4 images. The most
commonly used algorithms are Mixup, CutMix, Mosaic. Mixup fuses 2 random images
proportionally; CutMix cuts off a random part of an image and then fills the other data in the dataset
with this region pixel values; Mosaic is similar to CutMix but uses 4 random images. The third
category is GAN (Generative Adversarial Networks) based data generation methods. GAN and its
variants DCGAN, Pix2pix, Cycle-GAN can generate realistic data. Single graph processing
algorithms and multi-graph fusion algorithms can only alleviate the problem of insufficient data, while
deep learning generative adversarial methods can fundamentally solve this problem.

While the above data enhancement method focus on increasing the number of training data to help
solve the problem of insufficient training data, this paper aims at using the multi-operator
preprocessing method to enhance the features of the dataset. The key is in the feature extraction and
uses the edge detection operator to extract the edge features of the image before the object detection
algorithm is trained to reduce the noise in order to improve the accuracy of the object detection
algorithm.

3. Research Methodology
The main idea of this paper is to feature enhance the dataset using different edge detection operators,
put the enhanced data into a deep learning based object detection algorithm for training, and test the
trained model on the validation set. In this paper, we first introduce the edge detection operators, the
SSD object detection algorithm and the dataset respectively, and then introduce single-operator
experiment, multi-operator serial experiment and multi-operator parallel experiments according to the
different combinations of operators. In the end, we describe and analyze the various experiments and
results performed.

3.1. Edge Detection Operators Introduction
Edge detection is the detection of the local characteristics of image discontinuities, and the local
characteristics of discontinuities refer to the sharp changes in the surrounding pixel values. In this
paper, five operators that can perform edge detection are selected for testing, namely Robert operator,
Prewitt operator, Sobel operator, Laplacian operator, and Canny operator.

3.1.1. Robert. The Robert operator finds edges by local difference and detects edges by approximating
the gradient magnitude by the difference of two adjacent pixel points that are diagonal to each other.
This operator includes horizontal and vertical models as shown in Equation 1.

\[ d_x = \begin{bmatrix} -1 & 0 \\ 0 & 1 \end{bmatrix}, d_y = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix} \] (1)

As can be seen from the model above, the Robert operator is biased to enhance image edges at plus
or minus 45°, which means it can detect edges diagonally better than in any other directions, but lacks
the ability to suppress edges.

3.1.2. Prewitt. The Prewitt operator uses the difference of pixel values within a specific region of the
image to achieve edge detection of the object. The idea is to perform a neighborhood convolution with
the image using two models, one of which detects horizontal edges and the other detects vertical edges,
as shown in Equation 2 respectively.
The Prewitt operator uses a $3\times3$ model, $d_x$ is for non-normalized mean smoothing of the image in the vertical direction with the difference in the horizontal direction; $d_y$ is for non-normalized mean smoothing of the image in the horizontal direction with the difference in the vertical direction.

3.1.3. Sobel. The Sobel operator is a discrete differential operator with a wide range of applications. This operator calculates the approximation of the image brightness and darkness, and the specific point in the region that exceeds the threshold is recorded as an edge according to the brightness of the adjacent pixels at the edge of the image. The horizontal and vertical models of Sobel are shown in Equation 3.

$$d_x = \begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix}, \quad d_y = \begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$  \hspace{1cm} (3)

Sobel adds weights to Prewitt so that pixels that are close together have a larger impact and pixels far away have a smaller impact. The operator detects edges based on the weighted difference between the four neighboring pixel values and the extreme pixel value at the edge of the object in the image. The Sobel operator has a smoothing effect on the noise and produce more accurate edge localization.

3.1.4. Laplacian. Laplacian operator is a second order differential operator. Laplacian operator compares the gray value of the central pixel point with the neighboring pixel points in an image, and raises the center value if the center is high, and lowers it vice versa. The effect of sharpening the edges is achieved by enhancing the difference between the gray value of the center pixel and the surrounding pixels. This operator can be divided into four-field models and eight-field models. The four and eight represent the number of directions the model calculates the gradient around the center. For example, the four-field model used in this project calculates the gradient for the four directions of top, bottom, left and right, and its model is shown in Equation 4.

$$H = \begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$  \hspace{1cm} (4)

The Laplacian operator can be convolved with the image in the following three cases: 1) when the center pixel and the domain pixel have the same gray value, the convolution result is 0, and the image appears black; 2) when the center pixel is higher than the domain pixel gray value, the convolution result is positive, and the larger the absolute value of this number, the brighter the image is (when the pixel is equal to 255, the image appears white); 3) when the center pixel is lower than the gray values in its domain, the convolution result is negative. This negative number is added to the original center pixel gray value after appropriate attenuation. The Laplacian operator can accurately highlight the image edges, but it also enhances the noise.

3.1.5. Canny. The Canny operator is a multi-stage operator, and its implementation is listed as the following key steps: 1) Image noise reduction. First convolution operation is performed on the original image data with Gaussian model, which is also known as Gaussian noise reduction. 2) Calculate the image gradient. Use the first order differential partial derivative to calculate the size and direction of the gradient; 3) Non Maximum Suppression. In layman's terms, Non Maximum Suppression is to find the maximum value among the neighboring pixels and suppress the non-maximum values. 4) Double threshold screening. The algorithm sets a high threshold and a low threshold, points below the low threshold will be determined as non-edge directly, points above the high threshold will be determined
as edge directly, and pixel points between the high and low thresholds will be determined as edge if 
they are adjacent to the edge, and non-edge if they are not.

3.2. Object Detection Algorithms and Dataset Introduction

3.2.1. Object Detection Algorithm Introduction. The SSD algorithm has the advantages of its accurate 
detection and fast speed, and is now widely used in industry[24]. The SSD algorithm was proposed by 
W Liu, D Anguelov et al. in 2016, and surpassed both the then popular Faster-rcnn[25] and YOLO[26] in 
terms of accuracy and speed. When using Titan X, the SSD on the VOC2007 dataset result in an  
mAP[27] of 74.3% and a detection speed of 59 fps, which truly meets real-time monitoring. 

The structure of the SSD algorithm is shown in Figure 3.2. Six convolutional modules are added 
after the VGG-16[28] backbone network, and six different sizes of feature maps are fed into the 
classification layer at the same time, and a default box is found on each feature map to achieve  
detection of targets of different sizes. The default boxes are matched and selected by best jaccard overlap[20] and Hard Negative Mining[25], and the loss function of the model is calculated accordingly.

3.2.2. Dataset Introduction. The dataset used in this paper is the LED chip dispensing defect dataset  
(see Figure 2), which mainly has three defects: black object, white object and bubbles. This dataset is 
provid ed by the partner company and contains 2200 single-channel grayscale sample images of  
256×256 pixels. The sample set contains 5257 bubbles, 2886 black objects and 331 white objects.

4. Experiments and Analysis

The experiment consists of three experimental schemes, single-operator preprocessing, multi-operator  
serial preprocessing, and multi-operator parallel preprocessing. The specific experimental schemes are  
as follows: 1) single-operator scheme: the data is processed by a single operator and then is passed  
into the object detection algorithm for training. It also selected several operators that do not perform as  
effectively and are improved according to the experimental results; 2) multi-operator serial scheme:
the data is processed by multiple operators in serial and then is passed into the object detection algorithm for training; 3) multi-operator parallel scheme: the single-channel data is processed by operators, merged into three-channel data and then is passed into the object detection algorithm for training. The data used in this paper is randomly divided into training and validation sets by a ratio of 5:1. The object detection algorithm uses the SSD in the MMDetection object detection framework. We set the maximum iteration of SSD to be 24 epochs, the initial learning rate to be 0.0001, and the momentum 0.9. The learning rate is reduced to one-tenth each time when the iteration reaches 16 epochs and 22 epochs. The training is stopped when the maximum number of iterations is reached.

4.1. Evaluation Metrics for Experimental Results
All the experiments in this paper have two evaluation metrics, namely the Miss Detection Rate (MDR) and Mean Average Precision (mAP). MDR is the ratio of the number of defects missed to the total number of defects, which can be a useful measure of the detection effectiveness of the object detection algorithm. mAP is a common measure of the object detection algorithm. mAP is the mean value of AP, where AP is the area enclosed by the P-R curve, P is the accuracy rate, and R is the recall rate. The formula for calculating P and R is shown in Equation 5 and 6, where TP is the number of positive cases detected correctly, FP is the number of positive cases detected incorrectly, and FN indicates the number of negative cases detected incorrectly.

\[
P = \frac{TP}{(TP + FP)}
\]

\[
R = \frac{TP}{(TP + FN)}
\]

4.2. Single Operator Scheme
In this scheme, the images processed by each of the five operators are passed into SSD model training as the experimental group, and the original images are passed into SSD model training as the control group. The effect of edge detection operator preprocessing on the model detection efficiency is summarized by comparing the mAP and MDR analysis of the five experimental groups with a control group.

| Dataset      | mAP  | MDR  |
|--------------|------|------|
| Original dataset | 0.561| 0.082|
| Sobel        | 0.700| 0.081|
| Prewitt      | 0.673| 0.073|
| Robert       | 0.487| 0.123|
| Laplacian    | 0.400| 0.218|
| Canny        | 0.294| 0.380|

From Table 1, it is shown that the Sobel operator and Prewitt operator have better processing effect, with 24.8% and 20% increase in mAP and maintained somewhat similar or slightly decreased miss detection rate. In contrast, the Robert operator, Laplacian operator and Canny operator are less effective, with decreasing the mAP value and increasing the MDR. This proves that edge detection operators like Sobel and Prewitt can indeed enhance the data and improve the accuracy of the object detection algorithm.

4.3. Single Operator Improvement Scheme
This section analyzes the reasons why the Robert operator, Laplacian operator and Canny operator do not work well, and improves them.
(1) Robert operator: The Robert operator detects the edge by calculating the difference within local pixel values, which is more effective for processing images with steep edges and low noise. However, because the overall pixel values of this dataset are low (99% of the pixel values are below 142 and 80% of the pixel values are below 96), the difference for pixel values between defective edges and the local area is relatively small and cannot be extracted precisely. Due to large amount of feature edge information is lost, we enlarge specific values in the Robert operator to extract as many defective edge features as possible. The modified Robert operator is shown in Equation 7.

\[
d_x = \begin{bmatrix} -5 & 0 \\ 0 & 5 \end{bmatrix}, \quad d_y = \begin{bmatrix} 0 & -5 \\ 5 & 0 \end{bmatrix}
\]

(7)

(2) Laplacian operator: This operator is characterized by accurate localization of the steep edge points in the image, but it is very sensitive to the noise and can easily lose the directional information of some edges, resulting in some discontinuity in edge detection. We guess that the reason that Laplacian operator did not perform as well is due to the large noise of the original image. Therefore, we added Gaussian noise reduction before the convolution of Laplacian operator to improve the processing effect.

![Figure 3 The effect of operator improvement.](image-url)
Canny operator: Canny operator is less affected by the noise. By observing the results of Canny processing, we found that the Canny operator lost a lot of information on the edge and can only extract a very small portion of the defective edge. The reason is that the overall pixel value of the original chip image is low. When double threshold screening is performed, many defective edges are directly identified as non-edge by low threshold. Therefore, the improvement of the Canny operator is to reduce the threshold value of the Canny operator in order to extract as many edges as accurately as possible for images with low overall pixel values.

To test the above improvement schemes, we conduct a comparison test using the original operator and the improved operator. The two sets of operators are processed separately and passed into the SSD model for training, and we evaluate whether the operator improvement scheme is correct in terms of both mAP and MDR. To differentiate the original and improved operators, the improved ones are labeled with the suffix X in the following section, such as RobertX and LaplacianX.

Analysis of the experimental data in Table 2 shows that by applying improvement schemes, the mAP of all three operators improved by 30.4% to 36%, and the missed detection rate decreased by 53.7% to 56.9% for all three operators, and the improvements achieved significant results.

| Operator  | mAP  | MDR  |
|-----------|------|------|
| Robert    | 0.487| 0.123|
| RobertX   | 0.635| 0.053|
| Laplacian | 0.400| 0.218|
| LaplacianX| 0.544| 0.101|
| Canny     | 0.294| 0.380|
| CannyX    | 0.389| 0.167|

4.4. Multi-operator Serial Combination Scheme

From the single-operator experiments, it is shown that the edge detection operator can indeed enhance the data. Therefore, it might be a reasonable assumption that if we apply another improved operators right after the previous improvement, we might get a further enhancement with the rest of the images.

To test this assumption, a multi-operator serial combination scheme is designed. In this section, we tested the two-operator and three-operator serial combinations. Another point worth noting is that the Robert operator, Laplacian operator and Canny operator we use in this experiment are all improved versions.

To begin with, the Sobel operator and the Prewitt operator are used as the initial operators, and one of the remaining 4 operators is added afterwards to form a two-operator experiment group. Then the two groups with the best results are selected to continue adding one operator to form a three-operator experiment group. The experimental results are shown in Table 3. Combining the results of this experiment with the results of the single operator experiment, we found that the single operator scheme has a high mAP and a low MDR compared to all the double operator combination schemes for that operator. The double operator scheme has a high mAP and a low MDR compared to all the corresponding triple operator schemes. The following might explain why multi-operator scheme does not perform as well as the single operator scheme: It is believed that the operator will enhance the edge and weaken the non-edge area when processing the image. Also, the edge information is largely amplified after experiencing serial processing of multi-operator, while the non-edge information almost disappears and the gradient become uniform, all of which cause difficulties in object detection. Therefore, we concluded that the multi-serial operators is not an effective enhancement scheme.
4.5. **Multi-operator Parallel Combination Scheme**

The input data of the SSD algorithm is RGB three-channel data, while the dataset used in this paper is a single-channel dataset. In the single-operator experiments and multi-operator serial experiments, the single-channel data is copied into other two channels to mimic a three-channel scenario, which resulted in the same processed output passed into the SSD model for training. On the contrary, the multi-operation parallel scheme takes different operators for each one of the channels, resulting in different channel output passed into SSD training model. In short, parallel processing uses three different processing results of the same data for different channels, and then pass the data to the object detection algorithm for training and testing.

### Table 3: Training results of multi-operator serial combination scheme.

| Algorithm scheme           | mAP  | MDR  |
|----------------------------|------|------|
| Sobel_Prewitt              | 0.616| 0.098|
| Sobel_RobertX              | 0.523| 0.100|
| Sobel_LaplacianX           | 0.519| 0.134|
| Sobel_CannyX               | 0.414| 0.187|
| Prewitt_RobertX            | 0.584| 0.085|
| Prewitt_LaplacianX         | 0.500| 0.186|
| Prewitt_CannyX             | 0.392| 0.117|
| Sobel_Prewitt_RobertX      | 0.501| 0.117|
| Sobel_Prewitt_LaplacianX   | 0.504| 0.154|
| Sobel_Prewitt_CannyX       | 0.338| 0.221|
| Prewitt_RobertX_LaplacianX | 0.385| 0.204|
| Prewitt_RobertX_CannyX     | 0.228| 0.305|

4.5.1. **Experiment with Different Channels Using the Same Operator.** In the multi-operator parallel combination scheme, three different channels of RGB need to be processed, in order to test if the same set of three operators, operated within different channels, have significantly different training results. In this paper, the order of operators is followed by R-G-B. For example, Original_Sobel_Prewitt means that the original image is fed to the R channel, Sobel operator is used to process the G channel image input, and the Prewitt operator is used to process B channel image input. The result of all multi-operator parallel combination schemes is shown in Figure 4.

Analyzing the experimental results in Table 4, we can get the following three conclusions: 1) From Figure 4, we can see that the original image has more non-edge information, and the channel in which the original image is placed in the scheme basically determines what color the non-edge part of the final image will be; 2) The range of the mAP value of control group 1 is 0.047, and the range of the missed detection rate is 0.012. We consider the range within 0.05 as tolerable difference, so we conclude that there is no significant difference between the same set of operators in different RGB channels; 3) Regarding conclusion 1, we made another set of control experiments without using original image to improve detection, since original images have large amount of non-edge information. The range of mAP between the three schemes in control group 2 is 0.018, and the range of missed detection rate is 0.018, which are also tolerable differences. Since there is no significant difference of mAP in different RGB schemes for the same operator combination, we will not compare different RGB channel schemes in the subsequent experiments.
Figure 4 Comparison chart of different RGB channel schemes.

Table 4 Training results of different RGB channel schemes.

| Control group | R channel | G channel | B channel | mAP   | mDR   |
|---------------|-----------|-----------|-----------|-------|-------|
| Control group 1 | Original  | Sobel     | Prewitt    | 0.707 | 0.068 |
|                | Prewitt   | Original  | Sobel     | 0.685 | 0.070 |
|                | Sobel     | Prewitt   | Original  | 0.732 | 0.058 |
| Control group 2 | Prewitt   | Robert    | Sobel     | 0.705 | 0.059 |
|                | Robert    | Sobel     | Prewitt    | 0.697 | 0.077 |
|                | Sobel     | Prewitt   | Robert    | 0.715 | 0.061 |

Analyzing the experimental results in Table 4, we can get the following three conclusions: 1) From Figure 4, we can see that the original image has more non-edge information, and the channel in which the original image is placed in the scheme basically determines what color the non-edge part of the final image will be; 2) The range of the mAP value of control group 1 is 0.047, and the range of the missed detection rate is 0.012. We consider the range within 0.05 as tolerable difference, so we conclude that there is no significant difference between the same set of operators in different RGB channels; 3) Regarding conclusion 1, we made another set of control experiments without using original image to improve detection, since original images have large amount of non-edge information. The range of mAP between the three schemes in control group 2 is 0.018, and the range of missed detection rate is 0.018, which are also tolerable differences. Since there is no significant difference of mAP in different RGB schemes for the same operator combination, we will not compare different RGB channel schemes in the subsequent experiments.
4.5.2. Canny's Experiment and Its Contrast Experiment with Improved Operators. Among the five edge detection operators selected in this paper, only the Canny operator is a multi-order operator, which has additional steps such as Non Maximum Suppression and double threshold screening compared with the other four operators. Using the Canny operator in parallel with other operators, the edges extracted by the Canny operator are fine and sharp, which is very different from the processing effect of the other differential operators. Since the effect of Canny operator in multi-operator parallel experiments is not satisfactory, we did not use the multi-operator parallel combination scheme containing Canny operator for the experiments in the subsequent experiments.

In the single operator experiments, we have improved the Robert operator and Laplacian operator to obtain the RobertX operator and LaplacianX operator. Previously, we have concluded that the improved operator works better in the single operator experiments. The purpose of this set of experiments is to compare the effect of the original operator with the improved operator in a parallel scheme.

![Comparison of parallel schemes before and after algorithm improvement.](image)

**Table 5** Training results of parallel scheme before and after algorithm improvement.

| Algorithm scheme                  | mAP | MDR  |
|-----------------------------------|-----|------|
| Sobel_Prewitt_Laplacian           | 0.537 | 0.109 |
| **Sobel_Prewitt_LaplacianX**      | **0.584** | **0.077** |
| Sobel_Prewitt_Robert              | 0.610 | 0.080 |
| **Sobel_Prewitt_RobertX**         | **0.715** | **0.061** |

Analysis of the experimental data in Table 5 shows that in the parallel scheme, the improved operator scheme mAP obtains 8.8% and 17.2% improvement, and the missed detection rate is reduced by 29.3% and 23.8%. It has shown there is a significant enhancement. Therefore, in the subsequent experiments, we no longer used the original operator but adopted the improved operator for the parallel scheme.
4.5.3. **Comparison of Several Multi-operator Parallel Schemes.** We designed and experimented with 10 different sets of multi-operator parallel combination schemes, and the experimental results are shown in Table 6. The experimental results show that: 1) the LaplacianX operator works very poorly, except for the LaplacianX_RobertX_Original group. All the combinations containing the LaplacianX operator have an mAP lower than 0.672 and a MDR higher than 0.072; 2) The combination where the original image exists and does not contain the LaplacianX operator works well, with all mAPs above 0.731 and all MDR below 0.061 - we believe that this is because the original image contains more information. 3) The RobertX_Sobel_Original combination has the best enhancement, and the data processed by this set of operators improves the mAP by 34% compared with the original data and reduces the MDR by 35%, achieving the best result for all experiments in this paper.

| Algorithm scheme                  | mAP  | MDR  |
|-----------------------------------|------|------|
| Sobel_Prewitt_Original            | 0.732| 0.060|
| LaplacianX_Prewitt_Original       | 0.652| 0.079|
| RobertX_Prewitt_Original          | 0.749| 0.057|
| **RobertX_Sobel_Original**        | **0.752** | **0.053** |
| LaplacianX_Sobel_Original         | 0.664| 0.073|
| LaplacianX_RobertX_Original       | 0.731| 0.064|
| Sobel_Prewitt_RobertX             | 0.715| 0.061|
| Sobel_Prewitt_LaplacianX          | 0.584| 0.077|
| Sobel_RobertX_LaplacianX          | 0.671| 0.083|
| Prewitt_RobertX_LaplacianX        | 0.670| 0.086|

5. **Conclusion**

This paper mainly investigates the impact of edge detection operator processing on detection accuracy in industrial chip defect detection scenarios, using five operators, Robert, Prewitt, Sobel, Laplacian and Canny, and the SSD model for the experiments. The whole process is divided into three parts: processing the data through a single operator; processing the data through multiple operators serially; single-channel data is processed by operator and then merged into three-channel data, and then all the data are passed into the SSD model respectively for training. Through the experiments, we obtained the following conclusions: 1) some single-operator can enhance the images. 2) some multi-operator parallel schemes enhanced images, but the multi-operator serial scheme cannot enhance the images; 3) the best enhancement scheme is the three-channel data composed of the data processed by RobertX, Sobel operator and the original data.

**Acknowledgments**

This work was supported by the National Natural Science Foundation of China (61602146) and the National Basic Research Program of China (2017YFB1402200) and the Key Science and Technology Program of Anhui Province, China (1604d0802009).

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