Extremal Region Analysis based Deep Learning Framework for Detecting Defects

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Abstract—A maximally stable extreme region (MSER) analysis based convolutional neural network (CNN) for unified defect detection framework is proposed in this paper. Our proposed framework utilizes the generality and stability of MSER to generate the desired defect candidates. Then a specific trained binary CNN classifier is adopted over the defect candidates to produce the final defect set. Defect datasets over different categories are used in the experiments. More generally, the parameter settings in MSER can be adjusted to satisfy different requirements in various industries (high precision, high recall, etc). Extensive experimental results have shown the efficacy of the proposed framework.

Index Terms—Defect Detection, Deep Learning, MSER, CNN, Binary Classification

I. INTRODUCTION

THE rapid development of automation technology has advanced the process of factory modernization. Advanced automation equipment helps factories produce better quality products more efficiently and reduce labor costs in the production process. The increasing upstream productivity necessitates downstream product quality inspections in industry. Almost all factories need to check the quality of their products before sending to market. Improving the efficiency and precision of product quality inspections has become an inevitable problem facing modern factories. Therefore, defect detection of products play a crucial role in ensuring quality and characteristics. An automated defect detection framework can effectively remove the effort from human involvement. Machine vision based methods [1], [2] have been implemented to inspect defects. Recently, with the development of deep learning, advanced CNN methods have achieved great success [3], [4], [5]. A CNN has been shown to have strong perception and nonlinear fitting abilities. Also, the explicitly described task-relevant feature extracting algorithms are not needed throughout the learning process. Deep learning based defect detection methods have gained more and more attention in recent years. Several applications [6], [7] have been proposed and various defect datasets [8], [9], [10], [11] have been created and established to help researchers develop more robust and accurate algorithms.

In general, there are still many obstacles in defect detection. One of the challenges is the diversity of products, making it difficult to generalize a framework to handle different types. Another rigorous problem is that defects vary in terms of types, textures and sizes. To solve these challenges, we develop a unified defect detection framework that combines traditional image processing methods with deep learning. Defect regions observed in products usually stick out from neighbors when utilizing proper imaging equipment, as shown in Fig. 1, for various types of defects from different defect datasets. MSER [12] is a method to perform blob detection in image processing applications. However, pure MSER is not able to find a suitable threshold for finding all defect regions with high recall. Traditional image processing methods are sensitive to disturbances and lack robustness. Our proposed framework utilizes MSER to generate defect candidates with a customized threshold that captures all the defects, then adopts a capable binary CNN classifier to screen the final defects. We verify our proposed framework on 4 different defect datasets. The results strongly demonstrate the effectiveness of the proposed framework. It should be noted that our unified framework can be applied on various defects without changing models.

The rest of the paper is organized as follows: section II introduces our proposed method; section III describes the experiments; section IV concludes this paper.

Fig. 1: Samples from 4 different defect datasets. The red rectangles refer to the defects and the green rectangles refer to the normal regions. The rectangle size is 48 × 48.

II. METHOD
Our proposed method is comprised of two main steps. First, MSER is applied to generate defect candidates. Second, a binary CNN classifier is trained to screen the final candidates. The overall method framework is given in Fig. 2.

A. MSER for Candidates Generation

Defects observed in products usually differ from their neighbors. We can measure the differences between regions to guide the generation of defect candidates. MSER is used as a method of blob region detection in images, which can effectively generate qualified defect candidates. The threshold can be adjusted to satisfy customized requirements. MSER actually estimates the change between connected areas with a binary threshold in images. It is observed that defects often reveal small degrees of change. The MSER algorithm is detailed in Algorithm 1 with implementation examples shown in Fig. 3. It can be seen that the tolerance $\tau$ greatly impacts the generation of the defect candidates.

Algorithm 1 MSER algorithm

Input: gray image $I_g$, tolerance $\tau \in \mathbb{R}^+$

Output: binary image $I_b$

$t \leftarrow \delta, I_b \leftarrow 0$

for $t \in \{\delta, \delta + 1, \ldots, 255 - \delta\}$ do

Calculate binary images $I_t \leftarrow I_g > t$, $I_{t-\delta} \leftarrow I_g > (t + \delta)$, $I_{t+\delta} \leftarrow I_g > (t + \delta)$.

Get $M$ connected regions $\{Q_i, Q^\prime_{t-\delta}, Q^\prime_{t+\delta}| i = 1, 2, \ldots, M\}$ from $I_t, I_{t-\delta}, I_{t+\delta}$ respectively.

for $i \in \{1, 2, \ldots, M\}$ do

if $|Q^\prime_{t+\delta} - Q^\prime_{t-\delta}|/|Q_i| \leq \tau$ then

$I_b \leftarrow I_b \cup Q_i$

$i \leftarrow i + 1$

$t \leftarrow t + 1$

return $I_b$

B. Binary CNN Classifier

While the first step generates candidates of defects, in order to have high recall, the tolerance $\tau$ setting in MSER causes the candidate set to contain more than the defects. Therefore a binary classifier is needed to select the defects from the candidates. CNN [8], [9] has been proven extremely effective in classification tasks. A CNN based binary classifier is designed to perform the task.

Different from training on datasets like ImageNet [13] and Pascal-VOC [14] of natural daily images, the designed binary classifier fits into the characteristics of the defects.

Based on the understanding of the task and the data, we make three important design considerations. From observations of data, the defects are of low resolution. Pooling layers in traditional CNNs drop essential information when applied to low resolution images. To solve this particular problem, pooling layers are removed in our CNN model. As defects vary in types, textures and sizes, the network should capture small local features as well as global structural features. To achieve this, we apply $7 \times 7$, $5 \times 5$ and $3 \times 3$ kernel sizes in the first convolutional layer in a parallel scheme and concatenate all the outputs to get the fused feature maps. It is observed that the low-level and high-level semantic features both contribute to the classification of candidates. In order to preserve both the low-level and high-level features, we adopt the DenseBlock [15] to build our network. The dense connected patterns inside the DenseBlock makes the semantic information fully exchanged and retained.

The designed network of this paper is shown to be effective in the case of defect candidates classification. The network architecture is shown in Fig. 4.

During the training, the binary cross-entropy loss function applied is stated by:

$$
\mathcal{L} = \sum_{i=1}^{M} y_i \log(f(x_i)) + (1 - y_i) \log(1 - f(x_i)),
$$

where $\{x_i, y_i|i = 1, 2, \ldots, M\}$ denote the labeled training pairs and $f(\bullet)$ is the binary classifier.

Since the output of the classifier is the probability, a threshold $\omega$ is introduced to adjust the predictions by:

$$
\hat{y}_i = \begin{cases} 1, & \text{if } f(x_i) > \omega \\ 0, & \text{if } f(x_i) \leq \omega \end{cases},
$$

where $\hat{y}_i$ indicates the final prediction of the binary classifier.

III. EXPERIMENTS

Experimental setup, results and analysis are conducted in this section.

A. Datasets

We verify our proposed framework on 4 different defect datasets [8], [9], [10], [11]. Each dataset is split into 80%-20% training-testing parts. Data augmentations such as adding Gaussian noise, random flip and random crop are adopted. After the defect candidates generation process of MSER, we manually label the candidates to establish the datasets for the CNN classifier.

For measurements, we adopt precision and recall to evaluate the predicted results. The precision $P$ and recall $R$ are given by:

$$
P = \frac{TP}{TP + FP} \times 100\%$$

$$
R = \frac{TP}{TP + FN} \times 100\%,
$$

where $TP$, $FP$, $FN$ stand for True-Positive, False-Positive, False-Negative respectively.
Fig. 3: The defect candidates generated by MSER are marked by red points. The samples are from Road Crack \[9\] and Silicon Steel Strip \[11\] defect datasets.

Fig. 4: The designed binary CNN architecture for defect classification.

B. Implementation Details

All the programs are conducted in Python 3.6, running on a computer node with Intel Xeon E3 1230-v3 @3.4 GHz, Nvidia GTX 1080, 32 GB RAM, Ubuntu 16.04. The defect candidates size is cropped by $48 \times 48$. We use Pytorch \[16\] and Adam \[17\] optimizer with $\beta_1 = 0.9$, $\beta_2 = 0.99$, and the weight decay chosen is $10^{-4}$. The network is trained for 100 epochs. The learning rate is $10^{-4}$ at the first 50 epochs and decreased linearly to $10^{-6}$ within the following 50 epochs by $l_r = 10^{-4} - \frac{10^{-4}-10^{-6}}{50} (T - 50)$, where $T$ denotes the current training epoch.

C. Results

The defect detection results are shown in Fig. 5. It can be seen that our proposed framework performs the defect detection task well. The ablation analysis of our proposed method is stated in Table I. We compare existing methods with our proposed designs inside the CNN. Multi-Conv stands for the three parallel convolutional layers ($3 \times 3$, $5 \times 5$, $7 \times 7$). DenseBlock means the backbone network. Baseline means both Multi-Cons and DenseBlock are not included. The results are given in precision/recall format. Our proposed designs improve the precision performance significantly. The tolerance $\tau$ in Algorithm 1 and threshold $\omega$ in Eqn. 2 are adjusted to have 100% recall rate in order to capture all the defects.

IV. Conclusion

In this paper, we propose a unified defect detection framework that is comprised of two components. The first is the MSER defect candidates generation, and the second is the binary CNN classifier. Extensive experiments have demonstrated
### Table I: Ablation analysis for proposed and existing methods in precision and recall format.

| Dataset         | Baseline       | Multi-Conv     | DenseBlock     | Proposed       |
|-----------------|----------------|----------------|----------------|----------------|
| Rail            | 86%/100%       | 87%/100%       | 86%/100%       | 92%/100%       |
| Road            | 83%/100%       | 89%/100%       | 87%/100%       | 91%/100%       |
| Fabric          | 81%/100%       | 84%/100%       | 86%/100%       | 91%/100%       |
| Silicon         | 89%/100%       | 91%/100%       | 90%/100%       | 93%/100%       |

Fig. 5: The experiments on 4 different defect datasets. The detected defects are drawn in green rectangles.

The efficacy and accuracy of our proposed method. Different defect datasets are used to validate the generalizability of the proposed unified framework. It is noted that our framework has the essential tolerance and threshold to be adjusted to satisfy requirements (high recall), and can achieve 100% recall and considerable high precision on the datasets.

The future research lies in incorporating the segmentation based methods to enlarge the application scope.

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