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# Automatic ROI Extraction in Casting Flaw Detection

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**Abstract**. Using a LoG operator to extract edges in casting flaw detection will produce many noise edges at the same time, which greatly affects the speed and precision of subsequent classification. In order to solve this problem, a method based on the maximum continuous subsequence algorithm has been developed as the preprocessing of casting flaw detection. Experiment shows that the method can effectively eliminate noise edges and preserve flaw contours as the ROI, which greatly reduces the subsequent processing.

**Keywords:** ROI extraction; Flaw detection; Maximum gray scale difference image; Maximum continuous sub-sequence algorithm

## 1. Introduction

Wheel castings are important components in the automotive industry. To control the quality of die castings, it is necessary to detect flaws using X-ray imaging. The manual analysis of the X-ray images is labour-intensive and tedious, and many automatic flaw detection methods have been proposed. They can be classified to three main groups as follows:

a) Approaches comparing the test image with an error-free image[1,2];
b) Approaches reconstructing the cast product using computer tomography[3];
c) Approaches without a prior knowledge of the cast's structure, such as pattern recognition[4], expert systems[5], artificial neural networks[6] or multiple view analysis[7].

The first group of approaches is simple in theory, but it requires an error-free image as a reference for each casting, and precise positioning between the reference image and the test image. The second one is complex and expensive, and is not suitable for large-scale industrial application. The last one is commonly used in industrial environments, especially the algorithm proposed by D Mery[4,7]. The algorithm segments closed and connected regions as the potential flaws, which are analyzed using flaw features and classified as regular structures or defects. The closed contours which are produced by the LoG kernel are crucial to the algorithm. Non-closed contours are discarded. But a lot of noise contours are produced while scrutinizing the contours for true flaws, since the LoG kernel is hypersensitive to the noise. What is worse, the noise contours tend to connect with true flaws' contours. This greatly aggravates the task of subsequent classifying and reduces its precision.

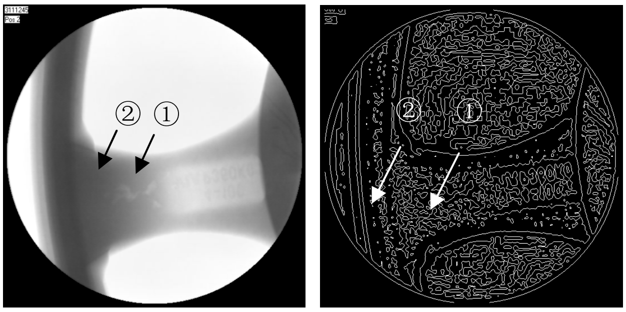
In order to improve the flaw detection procedure, this paper proposes a method of automatic ROI extraction as a preprocessing stage. It generates a smaller and more precise candidate set of potential flaws as the ROI. Experimental results show that this algorithm can effectively preserve all flaw structures while eliminating most of the noise edges, which greatly accelerates the subsequent processing.

The paper is organized as follows: In Section 2, the approach of automatic ROI extraction is described. The experiment results are presented in Section 3. Finally, Section 4 gives concluding remarks.

## 2. Algorithm

## 2.1. Feature of Casting Flaws

A casting image and its edge image obtained using the LoG operator is shown in Figure 1. As we can see, there are many closed contours in the edge image. Even the smooth regions in the casting image, such as the region pointed by symbol ① in Figure 1(a), can produce many closed contours, essentially produced by noise. As a result, there is a large candidate set of potential flaws and the subsequent processing will be time-consuming. It is necessary to eliminate noise edges and reduce the candidate set.




(a) (b)

Fig.1. A casting image (a) and its edge image obtained using LoG operator (b).

In X-ray examination, X-ray radiation is passed through the material under test, and a detector senses the radiation intensity attenuated by the material. A discontinuity in the material modifies the expected radiation received by the sensor. This phenomenon is called differential absorption[8]. As a result, in an X-ray image we can see that the defects, such as voids, cracks and bubbles, show up as bright features. Analyzing the two regions indicated in Figure 1, it is easy to see that the difference between the surrounding pixels' gray scale values and the region indicated by ② is less than for region ①. Since the contrast in the X-ray image between a flaw and a defect-free neighborhood in a casting is distinctive, this fact can be used in the preprocessing.

## 2.2. Maximum Gray Scale Difference Image

The maximum gray scale difference image (MGDI) is obtained using the testing image and its edge image. For each edge point in Figure 1(b), implement the following steps in its 3×3 neighborhood, as shown in Figure 2.

| | | |
|---|---|---|
| (x-1,y-1) | (x,y-1) | (x+1,y-1) |
| (x-1,y) | (x,y) | (x+1,y) |
| (x-1,y+1) | (x,y+1) | (x+1,y+1) |

Fig.2. Neighborhood of edge point.

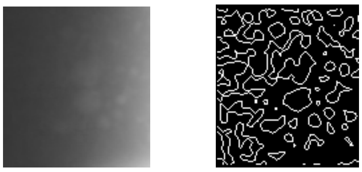
- Calculate the absolute value of gray scale difference in four directions, i.e. $\left|f(x-1,y-1)-f(x+1,y+1)\right|$, $\left|f(x,y-1)-f(x,y+1)\right|$, $\left|f(x+1,y-1)-f(x-1,y+1)\right|$, $\left|f(x-1,y)-f(x+1,y)\right|$
  Where $f(x,y)$ is the gray scale value of coordinate $(x,y)$ in Figure 1.
- Find the maximum value of the four calculated absolute values and assign it to the maximum gray scale difference image with a coordinate $(x,y)$.

The whole procedure of generating MGDI can be summarized using the following expression:

$$MGDI(x,y)=\max\begin{Bmatrix}\left|f(x-1,y-1)-f(x+1,y+1)\right|,\\ \left|f(x,y-1)-f(x,y+1)\right|,\\ \left|f(x+1,y-1)-f(x-1,y+1)\right|,\\ \left|f(x+1,y)-f(x-1,y)\right|\end{Bmatrix} \tag{1}$$

## 2.3. Maximum Continuous Sub-sequence Algorithm

A simple idea to eliminate noise edges and extract the ROI is to calculate the mean value of the maximum gray scale difference for each contour in the MGDI. With a suitable threshold this is easily achieved. However, this method cannot deal with the case in which the noise edge and flaw edge are joined together. Because in that case, the contour's mean value is unpredictable. An example is shown in Figure 3. So we propose a new method based on a maximum continuous sub-sequence algorithm (MCSA), which can easily handle this problem.



(a) Testing image (b) Edge image

Fig.3. A case in which noise edges and flaw edges joined together.

For each contour $i$ in MGDI, the MCSA is mainly described as follows.

*1) Record pixel coordinates of the contour*

Track along the contour, record pixel coordinates and the corresponding values in the MGDI into an ordinal circular list, named $L_i$. In the list $L_i$, each element is within its adjacent elements' 3×3 neighborhood.

*2) Predicate contour style*

Select a suitable threshold $\theta$ to separate flaw edge from noise edge. For each element of list $L_i$, subtract $\theta$ from the original value of the MGDI and update its value in the circular list. If the contour only has noise edges, all the list elements will be negative and can be discarded while if the contour only has flaw edges, all the list elements will be positive. If the contour has noise edges and flaw edges joined together, the list will have both positive and negative elements, where the positive elements stand for the flaw edge points and the negative elements stand for the noise edge points.

*3) MCSA*

In this step, we use the maximum continuous sub-sequence algorithm to deal with the third case above. Firstly, find the maximum continuous sub-sequence in the circular list until there are no positive elements in the list. Then save the found maximum continuous sub-sequence and discard the negative elements in the list.

*4) Link adjacent endpoint*

Check whether the saved contour corresponding to the maximum continuous sub-sequence is closed or not. If the saved contour is not closed and its endpoints are near to each other, we connect them to guarantee the contour's closure.

*5) Further process*

If the reserved contour has a large length, it will not be the flaw edge. Selection of a length threshold $l$ can further support the extraction of the ROI.

We combine the maximum gray scale difference image (MGDI) and maximum continuous sub-sequence algorithm (MCSA) to do ROI extraction in casting images. Experimental results are shown in the next section.

# 3. Exprimental Results

In this section, results of automatic ROI extraction of cast aluminum wheels using the approach outlined in Section II are presented. The parameters of our method have been manually determined, giving $\sigma = 2.5$ pixels for the LoG operator and $\theta = 4$, $l = 200$ as the thresholds. These parameters are not changed during these experiments. We do experiments on 80 casting images and for a large majority of them have perfect results. A portion of the experimental results are shown in Figure 4. To display the results clearly, we do an intensity inversion process on the edge images and the ROI images. Analysis of these results shows that most of the noise edges have been discarded while all the flaw edges have been saved as the ROI. Meanwhile, the problem where the noise edge and flaw edge are joined together has been solved.

To evaluate the performance of our method, we raise two criteria, called coverage and time acceleration. They are expounded as follows.

## 3.1. Coverage

Coverage is a performance criterion which shows how many real flaw contours are included in the processed ROI image. It is computed using the real flaw numbers in a test image and those in the processed image, as shown in expression (2).

$$Coverage = \frac{Number\ of\ real\ flaws\ in\ ROI\ image}{Number\ of\ real\ flaws\ in\ testing\ image} \qquad (2)$$

Coverage is an important criterion. If we don't have higher real flaw coverage, the subsequent processing is meaningless. Experiments show that the average coverage of the 80 images is 99%. Considering that some small and blurred flaws are unimportant for casting flaw detection, our method has a high performance in coverage. Partial results are shown in TABLE I which refers to Figure 4.

Table1. Performance of coverage

| Seq | Num of real flaws in test image | Num of real flaw contours in ROI | Coverage |
|---|---|---|---|
| (a) | 4 | 4 | 100% |
| (b) | 22 | 21 | 95% |
| (c) | 2 | 2 | 100% |
| (d) | 3 | 3 | 100% |
| (e) | 2 | 2 | 100% |

## 3.2. Time Acceleration

Time acceleration is the other important criterion to evaluate our method, because our final goal is to accelerate the subsequent processing. We use the ratio of contour number in edge image to that in the ROI image to indicate the time acceleration. This is shown in expression (3).

$$Time\ acceleration = \frac{Number\ of\ countours\ in\ edge\ image}{Number\ of\ countours\ in\ ROI\ image} \qquad (3)$$

The results are shown in TABLE Π, which indicates that our method can accelerate the subsequent processing by a factor of at least three producing a processing time more than three times faster than before.

Table 2. Performance of time acceleration

| Seq | Num of contours in ROI | Num of contours in edge image | Time acceleration |
|---|---|---|---|
| (a) | 40 | 219 | 5.48 |
| (b) | 89 | 325 | 3.65 |
| (c) | 20 | 173 | 8.65 |
| (d) | 38 | 344 | 9.05 |
| (e) | 30 | 323 | 10.77 |

# 4. Conclusion

In this paper, we introduce a new ROI extraction method for casting images using the maximum continuous sub-sequence algorithm. Experiments show that the algorithm can effectively eliminate noise edges and reserve flaw edges as ROI, greatly accelerating the subsequent processing.

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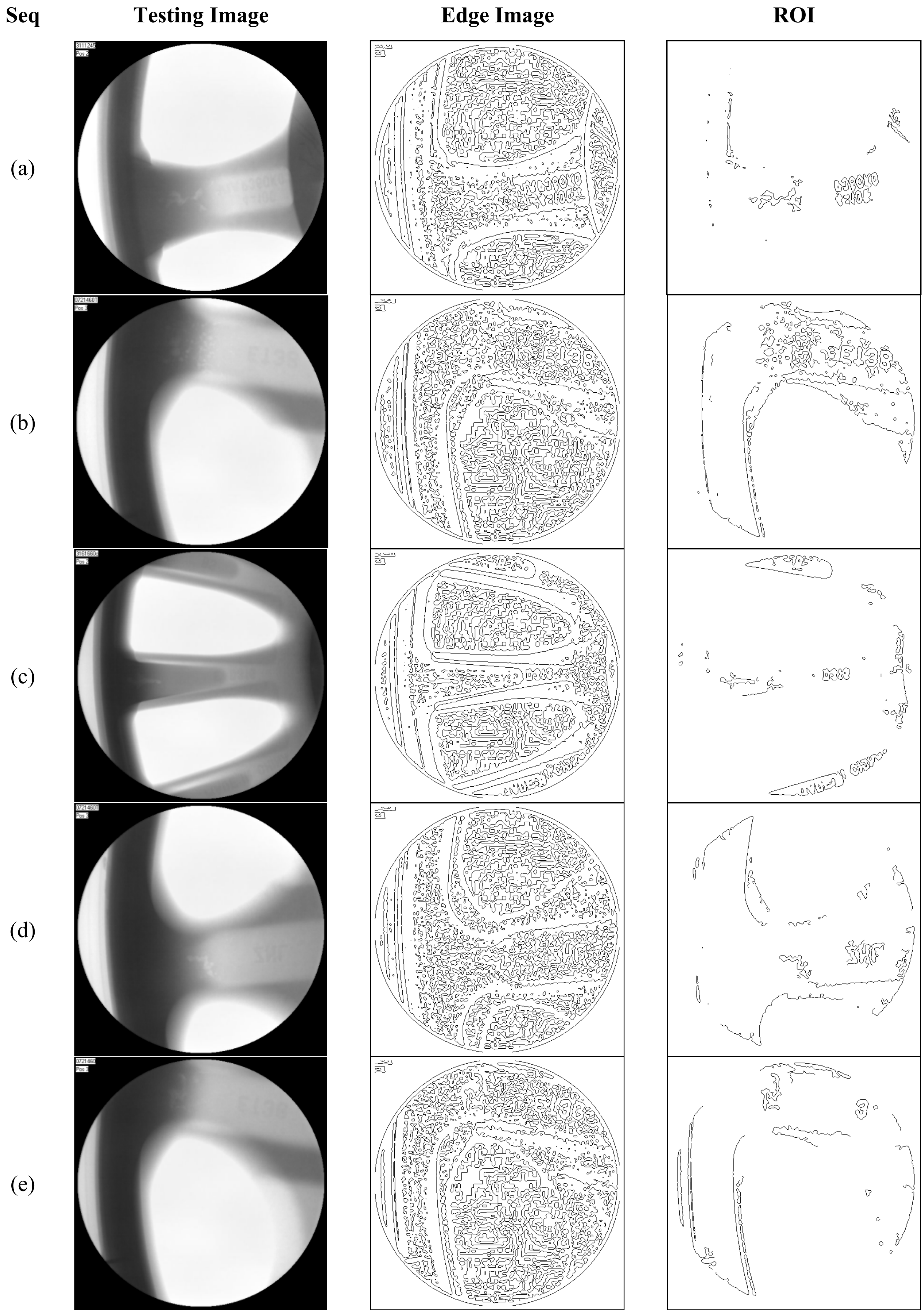


Fig.4. Experimental results.