

Automatic Detection Method for Casting Defects based on Gradient Features

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Abstract—In this paper, we propose an automated visual inspection method for casting defects. Automatic inspection systems have the potential to significantly improve quality and increase production rates. In our method, the contour discontinuity of casting product and machine-learning-based defect detection are utilized to detect defects on the surface of products. The peripheral vision and involuntary eye microvibration theories of the human visual mechanism in the field of the physiology of vision are modeled and applied in our feature extraction. By using several gradient features and different types of detector, we achieved robust casting defect detection.

I. INTRODUCTION

Recently, aluminium and steel castings have been used in various applications. In particular, the automotive industry employs aluminium casting products to make cars lighter and more energy efficient. The inspection of all safety-critical parts is applied as a standard, particularly in the automotive industry. However, the visual inspection of casting defects is manually carried out on the basis of human experience or intuition. Automatic inspection systems have the potential to significantly improve quality and increase production rates.

Several automated visual inspection methods have been proposed for casting products. In particular, the automated inspection of aluminium castings by the analysis of stationary radioscopic images taken at programmed positions of the specimens has been proposed [1]-[8]. Mery and Filbert proposed the automated inspection of aluminium castings by analysing stationary radioscopic images taken at programmed positions of the specimens [5]. However, this approach has high cost and processing time, and clearly is not suitable for mass production. The automotive industry presents a particularly challenging environment for computer-vision-based inspection. There is a demand for robust and accurate classifiers to perform accurate inspection under changing lighting conditions and with changing camera positions in a dirty environment. Miles and Surgenor proposed feature selection routines that can be used to improve the results of an ANFIS based classifier for automotive applications [9]. Although there is potential for good results with this approach, a long processing time is required to compute an accurate solution [10]. In addition, it is difficult to model defects on a casting surface since there are various

causes of defects. Therefore, a non-model-based casting defect detection method is required for practical applications.

On the other hand, a method of detecting salient regions in an image is useful for applications such as object recognition, adaptive compression, and image retrieval. Itti et al. [11] determined the center-surround contrast using a difference of Gaussians (DoG) approach. To detect a defect from a complex background, Arita et al. [2] proposed a defect detection method based on the rareness of several gradient features. However, these conventional methods were designed for defect detection from a surface having a periodic texture. Therefore, it will be difficult to apply them to casting defect detection.

In this paper, we propose an automated detection method for casting defects based on the visual physiology mechanism and machine learning. We attempt to model involuntary eye movement and the peripheral visual field, which are part of the human visual physiology mechanism, and to apply these models to feature extraction for casting defect detection. In our method, the contour discontinuity of casting product and machine-learning-based defect detection are utilized to detect defects on the surface of products. By using several gradient features and different types of detector, we achieve robust casting defect detection.

II. CASTING DEFECT DETECTION BASED ON GRADIENT FEATURES

A casting defect is an undesired irregularity in the metal casting process. They are categorized into gas pores, pouring metal defects, shrinkage defects, mold material defects, and metallurgical defects. It is difficult to construct a defect model because there are several causes of defects. They are undetectable by traditional image-processing algorithms since they are only slightly different from each other and are hidden in the background texture.

To resolve these issues, we propose a novel automated detection method for casting defects based on the visual physiology mechanism and machine learning. Generally, the visual inspection of casting defects is manually carried out and mainly based on human experience and intuition. It is necessary to analyze and quantify experience and intuition for modeling an inspection mechanism of inspector. We introduce part of the human visual mechanism into machine-learning-based casting defect detection.

We focus on the peripheral vision and involuntary eye microvibration theories. Peripheral vision is part of the vision that occurs away from the direct focus on attention. Involuntary microvibration is a movement of the eye that cannot

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be consciously controlled by humans. Control of the visual resolution and overlooking of the target field are important visual mechanisms and processes used by inspectors to detect salient defects in industrial products [13].

In this paper, we define a simple casting defect as follows:

- a hollow, crack or chip on a casting object such as a blowhole casting
- a blurred texture on a casting surface.

We propose defect detection based on this simple definition of a casting defect.

A. Defect Detection Method based on Contour Discontinuity

In this section, casting defect detection based on the contour discontinuity of casting objects is described.

1) *Preprocessing*: An example of a casting object is shown in Fig. 1(a). This object is part of an aluminium car engine.

First, the object surface in this image has high brightness under the light source. Therefore, the object region is extracted by thresholding the brightness. A dilation operation is applied to the extracted object region. The result of object extraction is shown in Fig. 1(b). In this image, white pixels correspond to the object. Next, Canny edge detection is applied to the original image to extract its edges. The extracted edge image is shown in Fig. 1(c). Finally, a logical AND operation between the extracted edges and the non-object region is performed to remove edges extracted from the surface texture. An example of a thickened object contour is shown in Fig. 1(d).

2) *Gradient feature extraction*: Let the intensity $I(i, j)$, $i = 0, 1, \dots, X - 1$, $j = 0, 1, \dots, Y - 1$, be an image of size $X \times Y$.

The gradient of $I(i, j)$ is defined by

$$g_x(i, j) = I(i + 1, j) - I(i - 1, j) \quad (1)$$

$$g_y(i, j) = I(i, j + 1) - I(i, j - 1). \quad (2)$$

The gradient magnitude is defined by

$$m(i, j) = |g_x(i, j)| + |g_y(i, j)|. \quad (3)$$

The gradient orientation is defined by

$$\theta(i, j) = \tan^{-1} \frac{g_y(i, j)}{g_x(i, j)}, \quad (4)$$

where $\theta(i, j)$ is in the range $[-\pi/2, \pi/2]$.

The original image is divided into some local regions (blocks). We set various value fort the block size, as shown in Figs. 2(a)-(c). Changing the block size is equivalent to controlling the visual resolution (the peripheral vision). In addition, in the process of block segmentation, standard points used for block division are shifted in various directions. The result of shifting the blocks in Fig. 2(b) is shown in Fig. 2(d). This approach is equivalent to involuntary eye microvibration.

An orientation histogram of the extracted object contour in each block is calculated. The orientation histogram h_o , which has a total of 180 bins numbered from 0 to 179, is defined by

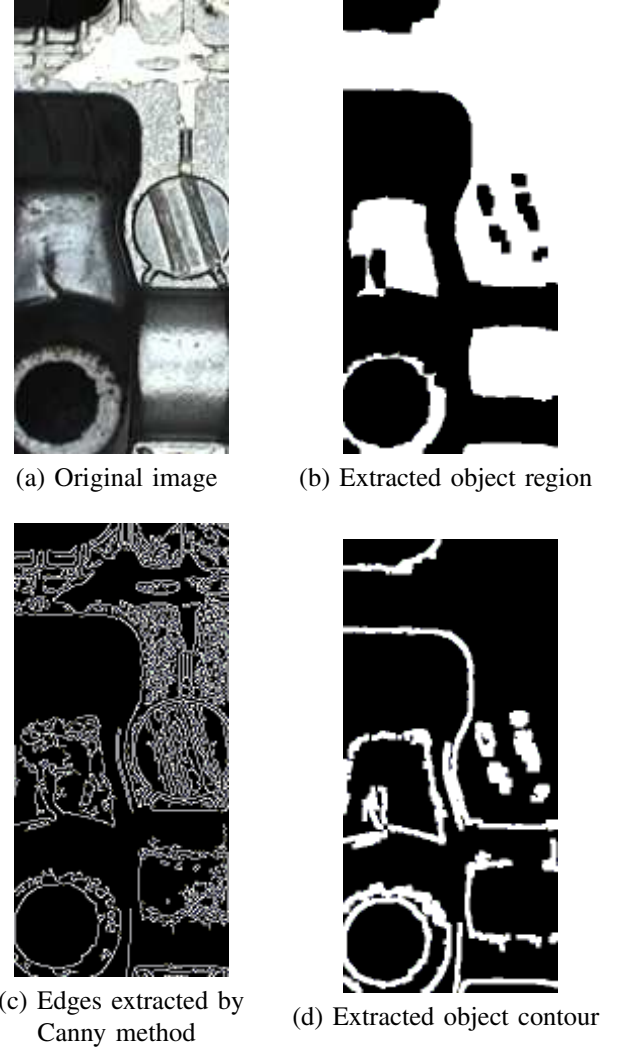


Fig. 1. Contour extraction of casting product

$$h_o(\theta') = \sum_{i=0}^{BS-1} \sum_{j=0}^{BS-1} \delta \left[\theta', \text{floor} \left(\frac{\theta(i, j) - 180}{2} \right) \right], \quad (5)$$

where BS is the block size, $\text{floor}()$ is defined as

$$\text{floor}(x) = x - [x], \quad (6)$$

and

$$\delta [i, j] = \begin{cases} 1 & (i = j) \\ 0 & (i \neq j) \end{cases}. \quad (7)$$

3) *Classifier*: In this method, a defect region is detected by a contour discontinuity of the casting object. The contour discontinuity CD of each block is defined by

$$CD = \sum_{i=0}^{179} |h_o(i) - \bar{h}_o|, \quad (8)$$

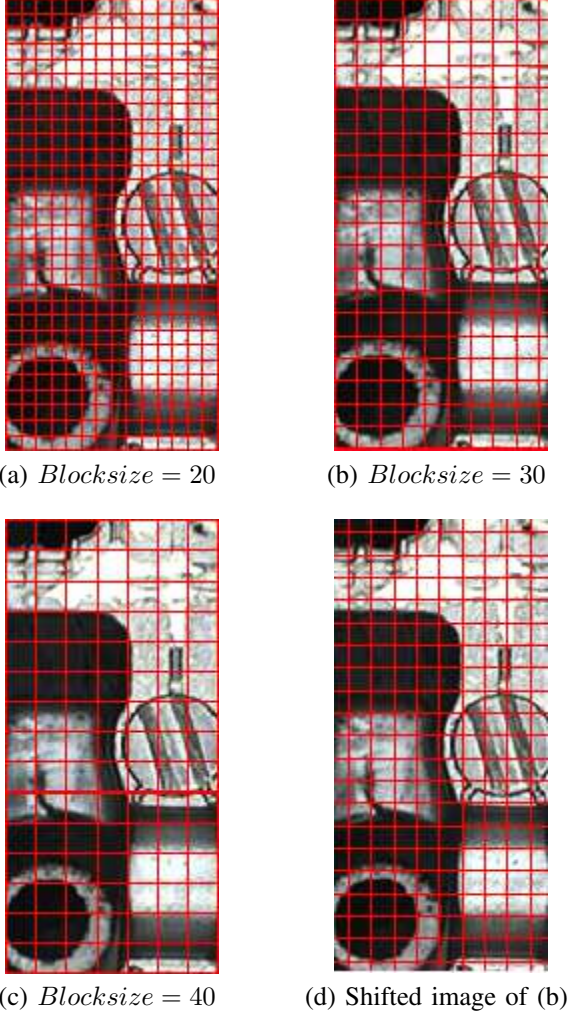


Fig. 2. Examples of block division

$$\bar{h}_o = \frac{\sum_{i=0}^{179} h_w(i)}{N}, \quad (9)$$

where N is the number of pixels in each block. Finally, each block is classified by thresholding with this value. To combine the classification results of all blocks, the defect detection result I_{com} based on the contour discontinuity is defined by

$$I_{com}(i, j) = \frac{1}{N_{BS}} \sum_{i=0}^{N_{BS}} f_{con}(i, j), \quad (10)$$

where N_{BS} is the number of blocks of a given size, and $f_{com}(i, j)$ is defined by

$$f_{con}(i, j) = \begin{cases} 1 & (\text{if } CD_x > \text{threshold}) \\ 0 & (\text{otherwise}), \end{cases} \quad (11)$$

where CD_x denotes the contour discontinuity of block x that includes pixel (i, j) . Therefore, $I_{com}(i, j)$ is the likelihood of a defect in pixel (i, j) .

B. Defect Detection Method based on Gradient Features of Surface Texture and Machine Learning

In this section, a machine-learning-based casting defect detection method using gradient features of the surface texture is described.

1) *Feature extraction*: As a preprocessing, the original image is divided into some local regions (blocks). A weighted orientation histogram of each block is calculated as a defect feature. The weighted orientation histogram h_{wo} with a total of 18 bins numbered from 0 to 17 is defined by

$$h_{wo}(\theta') = \sum_{i=0}^{BS-1} \sum_{j=0}^{BS-1} m(i, j) \cdot \delta \left[\theta', \text{floor} \left(\frac{\theta(i, j)}{20} \right) \right]. \quad (12)$$

The gradient magnitude is used to weight the orientation. This proposed feature represents the texture of the casting surface.

2) *Classifier*: In this paper, the support vector machine (SVM) based on the radial basis function (RBF) kernel is used for the classifier. The SVM is a two-class classifier constructed from the sums of a kernel function $K(\cdot, \cdot)$,

$$f(x) = \sum_{i=1}^n \alpha_i t_i K(x, x_i) + d, \quad (13)$$

$$\text{subject to } \alpha_i > 0 \text{ and } \sum_{i=1}^n \alpha_i = 0,$$

where n is the number of support vectors, t_i is the ideal output, and α_i is the weight of the support vector x_i . A backend RBF kernel is used to discriminate target languages. The RBF kernel is defined as follows:

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2), \quad \gamma > 0, \quad (14)$$

where γ is the kernel parameter estimated from the training data. In the SVM, $\gamma = 0.1$. Other parameters of the SVM are determined (e.g., $cost = 0.25$) experimentally.

Each block is classified by the learned SVM. To combine the classification results of all blocks, the defect detection result I_{tex} obtained by the SVM is defined by

$$I_{tex}(i, j) = \frac{1}{N_{BS}} \sum_{i=0}^{N_{BS}} f_{tex}(i, j), \quad (15)$$

where N_{BS} is the number of blocks of a given size, $f_{tex}(i, j)$ is the output of the SVM, which is 0 or 1.

Therefore, $I_{tex}(i, j)$ is the likelihood of a defect in pixel (i, j) .

III. EXPERIMENTS

A. Experimental Conditions

The test data set was provided by the Visual Inspection Algorithm Contest Committee [14] organized by the Technical Committee on the Industrial Application of Image Processing, Japan [15]. In this dataset, there are 52 images

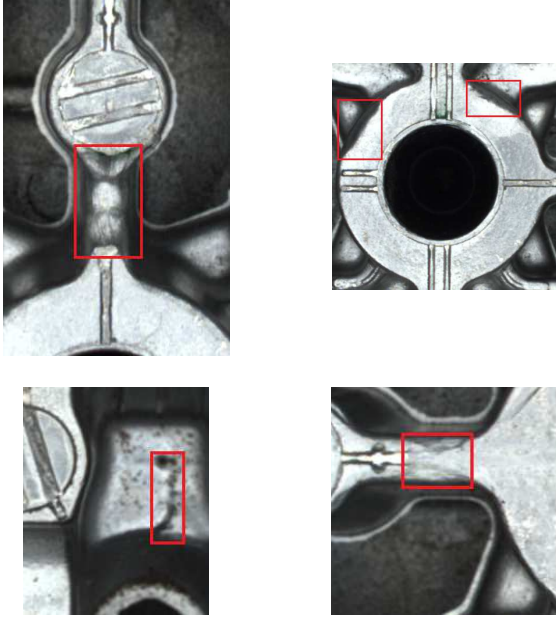


Fig. 3. Examples of casting images with casting defects

of a car engine casting taken from various angles. There are 30 images without defects and 22 images with a total of 27 defects. The regions of casting defects are indicated by rectangles, as shown in Fig. 3.

The block size used in block division was varied from 30[pix.] to 50[pix.] at 2[pix.] intervals. The block shift was set to 5[pix.]. In addition, the machine-learning-based method was evaluated by the leave-one-out cross validation method.

We also used a saliency region detection method proposed by Itti et al. [?] as well as the saliency-region-detection-based defect detection method proposed by Arita et al. [2] as a comparison method. We implemented our proposed method and the comparison methods with the support of the Intel OpenCV library using a PC with Microsoft Windows 7. The hardware platform for the experiment was a PC equipped with an Intel Core i7 3.4 GHz with 8 GB RAM.

In this paper, we combine the results of both proposed methods. The combined result I_{max} is defined by

$$I_{max}(i, j) = \begin{cases} 1 & (\text{if } \max(I_{con}(i, j), I_{tex}(i, j)) > th) \\ 0 & (\text{otherwise}) \end{cases} \quad (16)$$

where th is the threshold used to classify whether pixel (i, j) is a defect and $\max(x, y)$ is defined by

$$\max(x, y) = \begin{cases} x & (\text{if } x > y) \\ y & (\text{otherwise}) \end{cases} \quad (17)$$

B. Experimental Results

The results of defect detection based on contour discontinuity are shown in Figs. 4 and 5. In each figure, we show the original image with the correct defect regions, the result of the proposed method based on contour discontinuity, the

result of the proposed method based on surface texture, the result of combining the methods, and the result of both conventional methods. In these results for defect detection, lighter pixels mean that the likelihood of a defect region is high. In Fig. 4(a), the casting defect is a crack. The proposed method based on contour discontinuity was designed for the detection of cracks on casting objects such as blowhole castings. Therefore, these defects were correctly detected as shown in Figs. 4(b) and (d).

On the other hand, there is a casting defect in the form of a hollow and a chip on the casting surface in Fig. 5(a). The result of the proposed method based on surface texture correctly detected this defect in Figs. 5(c) and (d).

We show the results of all the tests in Table 1. The number of precisely detected defects and the number of overdetections are shown in this table. In addition, Th was employed to judge whether pixel (i, j) is part of defect region, $Corr$ is the number of defects detected correctly, and $Over$ is the number of overdetections. $Corr$ and $Over$ were manually counted by judging whether the center of gravity of each detected defect region was included in the given actual defect region after the threshold Th was applied to each detection result. It was found that all defects were correctly detected without over-detection. We thus confirmed the effectiveness of the proposed method for the detection of casting defects.

IV. CONCLUSIONS

In this paper, we proposed different automated detection methods for casting defects based on the visual physiology mechanism and machine learning. Experimental results showed the effectiveness of the proposed method. By using several gradient features and different types of detector, we achieved robust casting defect detection.

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TABLE I
RESULTS OF TESTS

Th	Proposed method I_{con}		Proposed method I_{tex}		Proposed method I_{mix}	
	$Corr$	$Over$	$Corr$	$Over$	$Corr$	$Over$
50	13	0	21	0	24	0
40	13	1	23	0	25	1
30	13	2	23	1	25	3
20	13	3	24	2	25	5
10	15	3	26	8	26	8

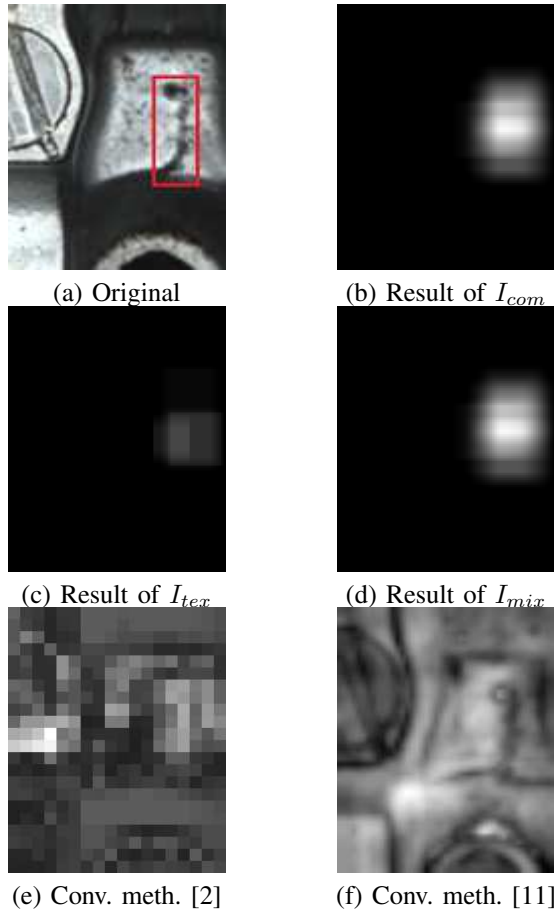


Fig. 4. Results of defect detection for a crack

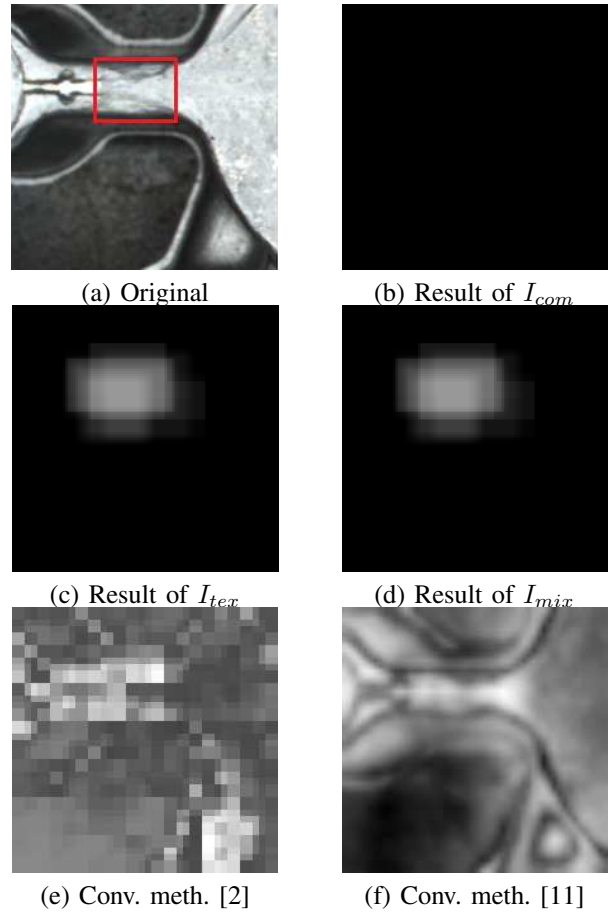


Fig. 5. Results of defect detection for a hollow and a chip

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