Improving Automatic Detection of Defects in Castings by Applying Wavelet Technique

Xiaoli Li, S. K. Tso, *Senior Member, IEEE*, Xin-Ping Guan, *Senior Member, IEEE*, and Qian Huang

***Abstract*—X-ray-based inspection systems are a well-accepted technique for identification and evaluation of internal defects in castings, such as cracks, porosities, and foreign inclusions. In this paper, some images showing typical internal defects in the castings derived from an X-ray inspection system are processed by some traditional methods and wavelet technique in order to facilitate automatic detection of these internal defects. An X-ray inspection system used to detect the internal defects of castings and the typical internal casting defects is first addressed. Second, the second-order derivative and morphology operations, the row-by-row adaptive thresholding, and the two-dimensional (2-D) wavelet transform methods are described as potentially useful processing techniques. The first method can effectively detect air-holes and foreign-inclusion defects, and the second one can be suitable for detecting shrinkage cavities. Wavelet techniques, however, can effectively detect the three typical defects with a selected wavelet base and multiresolution levels. Results indicate that 2-D wavelet transform is a powerful method to analyze images derived from X-ray inspection for automatically detecting typical internal defects in the casting.**

***Index Terms*—Castings, defects, image processing, wavelet transform, X-ray inspection.**

I. Introduction

NONDESTRUCTIVE testing (NDT) is widely used to detect and evaluate a variety of defects in industrial products. Nowadays, X-ray inspection is an established technique for identification and evaluation of internal defects, which has been applied to a wide range of industries such as inspection of microminiature electronic circuitries, light-alloy casting [1], welded seams [2], and heavy steel structures that are more than 100 mm thick [3].

In the last few decades, the demand for light-alloy castings for the automotive industry has increased dramatically. This is because the automotive industry is striving to manufacture lighter automobiles. This requirement makes it important to reduce the weight of the castings without compromising its structural integrity. The use of light alloys to replace steel in automobiles has increased the application of X-ray inspection in major casting facilities throughout the world [4]. Basically, the primary drives for X-ray automated inspection systems include elimination of manual inspection inconsistency due to human fatigue or other reasons, faster inspection rates, the need for more quantitative and thorough product evaluation, higher quality demands, and requirement for annotated records of all inspection decisions.

Unfortunately, most inspection systems in casting today are manually operated. The inspection quality depends on operator experience, and according to the variety of defects and their different features, the inspection process itself is time consuming and inefficient. Moreover, the nature of image formation and the poor image quality present many problems to a human inspector [5] and make the interpretation of the image content very difficult. Some new technologies on X-ray inspection for castings include improvements of the method used to produce the X-ray image, and modern computer hardware and associated software. These allow the X-ray inspection process to be carried out at a high speed and in a fully automatic mode [6]. Combining X-ray inspection with digital image processing and automatic image assessment is now the preferred approach for the continuous inspection of castings. Although a few major casting companies have installed X-ray automated inspection systems to carry out 100% inspection to ensure that structural quality standards are always met, identification of casting defect types is still done by a human observer.

Defects are characterized in X-ray images by local changes in the image intensity, resulting in corresponding local discontinuities in the gray values of the acquired image. The defect-detection process is essentially one of pixel classification, where the goal is to classify each image pixel as a defect or not. Currently, many methods may be considered for detecting casting defects, such as background subtraction, which is based on estimating a background image (which does not contain the defects) from the preprocessed image and then subtracting it from the preprocessed image to leave the residual image with defects only [7]–[9]. Matched filters have also been used to identify potential defects [10]. It is evident to detect defects of any type and any shape using a filter matching, a specific type of defect would not be suitable. Edge-detection techniques are not appropriate because of their high sensitivity to noise. Another important method is feature-based detection [11], [12], whereby each image pixel is classified as a defect or not

Manuscript received October 3, 2004; revised March 10, 2005. Abstract published on the Internet September 15, 2006. This work was supported in part by the National Natural Science Foundation of China under Grant 60575012, in part by the research unit CIDAM, City University of Hong Kong, and in part by the Hebei Education Foundation of China.

X. Li is with the Center for Networking Control and Bioinformatics, Yanshan University, Qinhuangdao 066004, China, and also with Cercia, School of Computer Science, University of Birmingham, Birmingham B15 2TT, U.K. (e-mail: xiaoli.avh@gmail.com; x.li@cs.bham.ac.uk).

S. K. Tso, retired, was with the Consortium for Intelligent Design, Automation, and Mechatronics, Department of Manufacturing Engineering and Engineering Management, City University of Hong Kong, Kowloon, Hong Kong.

X.-P. Guan is with the Center for Networking Control and Bioinformatics, Yanshan University, Qinhuangdao 066004, China.

Q. Huang is with the School of Electrical and Information Engineering, South China University of Technology, Guangzhou 510061, China (e-mail: eeqhuang@scut.edu.cn).

Digital Object Identifier 10.1109/TIE.2006.885448

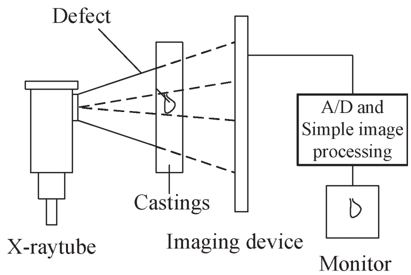


Fig. 1. Traditional X-ray inspection system in castings.

depending on features that are usually computed from a local neighborhood around the pixel. Usual features include local statistical descriptors (mean, standard deviation, skewness, kurtosis, energy, and entropy) [13] and localized wavelet decomposition [12]. Adaptive thresholding developed by Kehoe [14] could effectively be used to design a threshold based on the statistical analysis of a large population of intensity values taken from around each pixel to determine if the pixel is part of a defect region. Intelligence-based new methods have been explored, such as in [15]–[17]. In this paper, we will describe and examine the usefulness of three methods for the detection of typical defects in castings.

This paper is organized as follows. Section II introduces an X-ray inspection system used in casting. Methods of applying image processing to detect the defects in castings are presented in Section III, and the results obtained by these methods are shown in Section IV. Conclusions are given in Section V.

II. Overview of X-Ray Inspection System in Castings

The basic process of X-ray inspection for castings is introduced here. A collimated beam of ionizing radiation emitted from an X-ray tube passes through the castings being inspected. The X-ray energy level is attenuated in proportion to the material thickness and the presence of any void, inclusion, or discontinuity within the castings. After the beam passes through a casting, it impinges on to the imaging device, which could be either an image intensifier coupled to a charge-coupled device (CCD) camera or a digital imager. The image contains key information related to the internal structure of the castings. Then, the operator, or computer-system, extracts these images produced by the X-ray inspection system and classifies the castings as either normal or abnormal castings.

In recent years, the X-ray inspection systems applied in the casting industry appear to favor the use of a direct digital imaging device, such as a flat-panel amorphous silicon (a-Si) or amorphous selenium (a-Se) sensor array, or a linear diode array, to replace the X-ray image intensifier coupled to a CCD camera as the intensifier is relatively heavy, has limited dynamic range, is liable to image blooming and has a relatively high noise level. The direct digital imaging device is suitable for the fully automatic mode. In addition, it offers a larger inspection area, a substantial improvement in contrast capability, and a lighter and more robust construction. A traditional X-ray inspection scheme for castings is shown in Fig. 1.

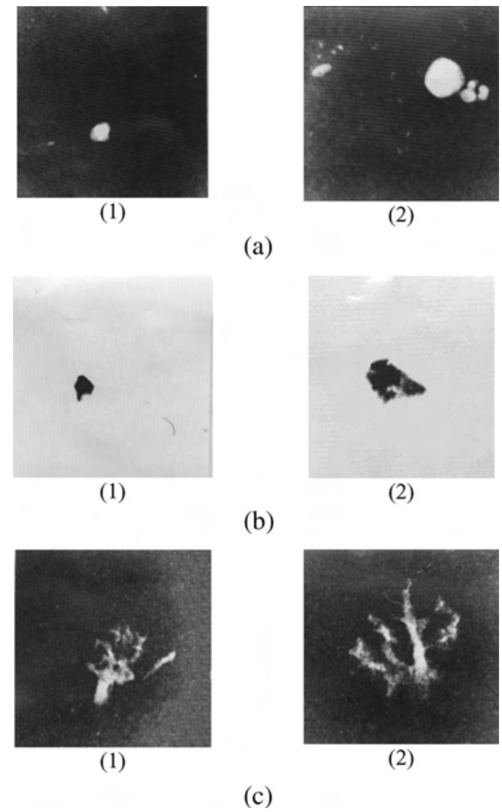


Fig. 2. Internal defects in castings. (a) Air-hole defects. (b) Foreign-object defects. (c) Shrinkrage-cavity defects.

Defects in castings include air holes, foreign-particle inclusions (slag and sand), shrinkage cavities, cracks, wrinkles, casting fins, and abnormal microfracture. In general, the ones that appear on the external surface of castings, such as cracks, are more easily detected; operators can inspect and identify these defects visually or by sense of touch. Some methods have been proposed for automatic detection of external defects [18], [19]. On the other hand, the detection of internal defects in castings, such as air holes, cracks, and microfracture, is a difficult task for operators. One traditional method is to discover the internal defects by cutting up the castings; obviously, this "destructive" process of finding the internal defects in castings is time consuming and requires skillful operators. However, as internal defects in castings may lead to serious accidents, a variety of nondestructive methods have been developed for detecting such defects [20], [21].

In this paper, the key to computerized X-ray inspection is to find a method to analyze the inspected images so as to detect any internal defects. The typical defects of porosity cavities and nonmetallic inclusions are chosen for the present paper because these internal defects generally exist in casting. Porosity cavities consist of air holes and shrinkage cavities, while foreign inclusions represent impurities present in the parts during casting. Some images showing these defects are shown in Fig. 2. These digital images have a pixel size of 30 mm $\times$ 30 mm with 256 gray levels. The gray-level variation due to these typical defects can be seen in Fig. 2. It is noticeable that the foreign object defects in Fig. 2 are plotted by their inversion, so the objective detected can be enhanced.

III. Automated Detection of Defects

Automated detection and evaluation of defects in castings are currently gaining importance. This section intends to develop a new method to automatically process the produced radiographic images. An important problem for the new inspection system in each inspection cycle is the enhancement of the image to facilitate accurate detection of defects in the casting. In this section, preprocessing, three methods for defects detection, and automated decision are presented.

A. Preprocessing

Preprocessing prepares the acquired raw digital image for the main defect-detection stage by reducing noise, correcting for background trends (e.g., shading correction), and removing geometric structures that otherwise would adversely affect the main processing stage. Noise in the X-ray image is characterized by its high spatial frequency and its lack of spatial correlation [22]. Noise reduction is typically carried out by temporal or spatial averaging techniques [22]. Depending on the noise characteristics, filters such as median filters (for impulsive noise), Gaussian smoothing filters (for Gaussian white noise), adaptive smoothing filters (for signal-dependent white noise), and Kalman filters (for colored noise or signal-dependent colored noise) can be employed for more complex noise-reduction tasks.

In this paper, the median filter and Wiener filtering are found to be adequate to preprocess these images. Median filters have an advantage of smoothing the images while retaining the edges to a large extent, but they are nonlinear so that they are difficult to analyze. However, they are easy to implement and are extremely useful in removing impulsive noise [23], [24]. A median filter can have any shape and scan over the entire image, with each output point corresponding to the median of the data located in the filter at each input point. A 3 × 3 median filter is found to provide adequate smoothing for the casting images studied. To improve these images and reduce the noise effects, Wiener filtering [25] is additionally applied to preprocess these images. Fig. 3 shows the result of Fig. 2 with both aforementioned filters; the performance of images has been enhanced based on the visual identification.

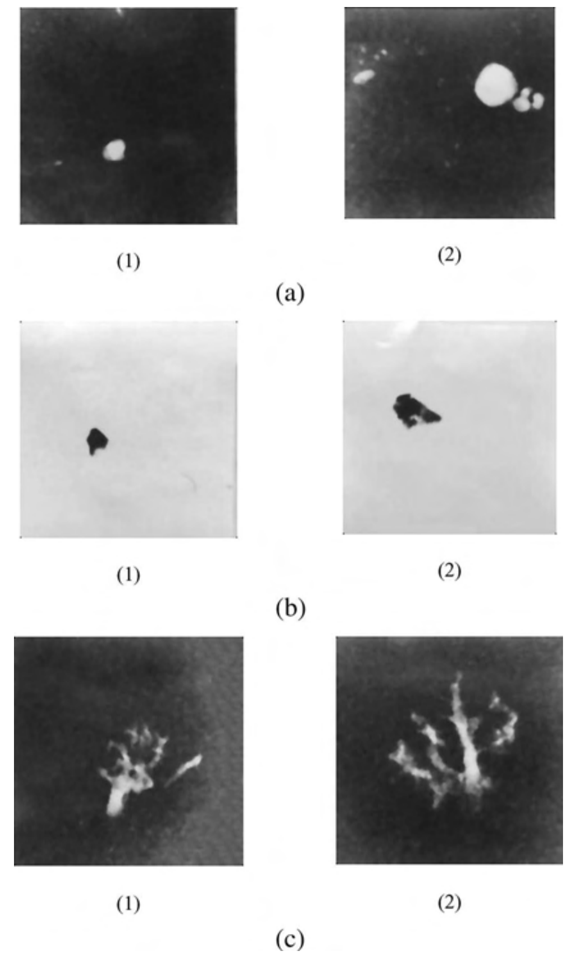


Fig. 3. Internal defects by preprocessed in castings. (a) Air-hole defects. (b) Foreign-object defects. (c) Shrinkrage-cavity defects.

B. Three Methods Selected for Detecting Defects in Casting

1) Second-Order Derivative and Morphology Operations: Derivative-based operations are fundamental operations in image processing, and one or more spatial derivatives of the image can be used [26]. Since a digitized image is not a continuous function $f(x, y)$ of the spatial variables but rather a discrete function $f[m, n]$ of the integer spatial coordinates, the algorithms we are applying can only be seen as approximations to the true spatial derivatives of the original spatially continuous image. Meanwhile, after taking a derivative, the high-frequency noise will tend to be emphasized in the resulting image.

The second-derivative operation computes the higher order derivatives of the two variables in the image processing. The second derivative is defined as

$$\begin{aligned}\nabla^2 f &= \frac{\partial^2 f}{\partial x^2}\,\vec{i}_x + \frac{\partial^2 f}{\partial y^2}\,\vec{i}_y \\ &= (h_{2x} \otimes f) + (h_{2y} \otimes f) \qquad (1)\end{aligned}$$

where h_{2x} and h_{2y} are second-derivative filters. The basic choice for filters h_{2x} and h_{2y} is given by $[h_{2x}] = [h_{2y}]^T = [1 \;\; -2 \;\; 1]$. According to the images in this paper, the detailed algorithm of the second-derivative method is given as [27]

$$\begin{aligned}g(m,n) = \max\{ & f(m-2,n-1) - 2f(m,n-1) \\ & + f(m+2,n-1) + f(m-2,n) \\ & - 2f(m,n) + f(m+2,n) \\ & + f(m-2,n+1) - 2f(m,n+1) \\ & + f(m+2,n+1), f(m-1,n-2) \\ & - 2f(m-1,n) + f(m-1,n+2) \\ & + f(m,n-2) - 2f(m,n) \\ & + f(m,n+2) + f(m+1,n-2) \\ & -2f(m+1,n) + f(m+1,n+2)\} \qquad (2)\end{aligned}$$

where $f(m, n)$ is the gray value of pixel (m, n).

The images consist of a set of elements that collect into groups that have a two-dimensional (2-D) structure. Various mathematical operations on the set of pixels called mathematical morphology can be used to enhance specific aspects of the shapes so that they might be counted or recognized. Mathematical morphology or simply morphology is a set-theoretic approach to change the shape of regions and segments of images. It is a useful basis for the design of algorithms for segmentation, preprocessing, object recognition, and development of higher level algorithms as well [28]–[30]. In particular, this operation can be used to describe or analyze the shape of a digital object in image processing.

Basic operation of morphology includes dilation and erosion. Consider an image $\mathbf{A}$ with discrete variables $a[m,n]$ and structuring elements $\mathbf{B}$ with discrete variables b. We may define the fundamental mathematical morphology operations dilation and erosion from the Minkoski operations [31] given by

$$\text{Dilation}: D(\mathbf{A},\mathbf{B}) = \bigcup_{b\in\mathbf{B}} (\mathbf{A}+b) \tag{3}$$

$$\text{Erosion}: E(\mathbf{A},\mathbf{B}) = \bigcap_{b\in\mathbf{B}} (\mathbf{A}+b). \tag{4}$$

It is known that dilation can cause objects to dilate or grow in size and erosion can cause objects to shrink. However, we should realize that the amount and the way that they grow or shrink depend on the choice of the structuring elements. Dilating or eroding without specifying the structural element makes no more sense than trying to low-pass filter an image without specifying the filter. The two most common structuring elements are the four-connected and eight-connected sets N4 and N8 [31].

2) Row-by-Row Adaptive Thresholding: For every horizontal line in the image, an array a_i is created $(0 \le i \le 200)$. This array contains the original gray-level values from the line currently being scanned in the image. From this, a second array b_i is created to represent the expected gray levels of the pixels if there are no defects in the image of the casting. Array b_i is calculated from the gray levels of the surrounding pixels. The calculation details are listed as follows [30].

Step 1) $b_i = a_i$.
Step 2) If $b_i < low$, then $b_i = low$. If $b_i > high$, then $b_i = high$.
Step 3) $b_i = \sum_{n=-m}^{m} b_{i+n}/7$ (herein, $m = 3$).
Step 4) If $b_i > b_{i-1}$, then $b_i = b_{i-1} + c$. If $b_i = b_{i-1}$ then $b_i = b_{i-1}$; otherwise $b_i = b_{i-1} - c$

where m is the window width and c is a positive integer.

The aim of Step 2) is to replace very large and very small gray-level values with a more intermediate gray level, which ensures that the gray levels will not greatly affect the averaging calculations. Step 3) is used to smooth b_i by using simple averaging. To avoid b_i from being affected by large deviations in gray level, the rules of Step 4) are used in this paper. It must be emphasized that the parameters low, $high$ and c are determined empirically. In this paper, these parameters are chosen as $low = 60$, $high = 150$, and $c = 0.5$. Parameter c ensures that large changes in gray level are not allowed to affect significantly the expected values.

3) Wavelet Transform Technique: The 2-D wavelet analysis [24], [32], [33] is used to process the preprocessed images. The 2-D wavelet decomposition operation consists of filtering and downsampling horizontally using a one-dimensional low-pass filter L and high-pass filter H to each row in the image f and produces the coefficient matrices f_L and f_H. Vertical downsampling follows, using the low-pass and high-pass filters L and H to each column in f_L and f_H, and produces four subimages f_{LL}, f_{LH}, f_{HL}, and f_{HH} for one level of decomposition [24]. The f_{LL} is a smooth subimage representing coarse approximation. The pyramid decomposition algorithm [24] is used to iterate on the smooth subimage f_{LL}. As will be described, in this paper, the bi-orthogonal wavelets (bior3.7) [24] are used to decompose the images, to obtain a subimage f_{LL}^1, and then to decompose the subimage f_{LL}^1 to get the second subimage f_{LL}^2. Finally, the subimage f_{LL}^2 become the object to be analyzed.

In the wavelet-based method, there are two main factors affecting the processed results, namely 1) selection of wavelet bases and 2) selection of the number of multiresolution levels. First, the different wavelet bases Harr, Dauble D4, and bi-orthogonal bior3.7 [24] are evaluated. Results from the study show that the choice of wavelet bases has only small effects on the detection for these images; all wavelet bases can enhance the defects in the images. However, bi-orthogonal wavelet bior3.7 generally outperforms the other wavelet bases in terms of detection effectiveness and is selected for application to defect detection.

Second, the number of multiresolution levels is considered. Based on the experimental results, too small a number of multiresolution levels cannot sufficiently separate the defects from the subimages; too large a number of multiresolution levels results in some false alarms. Based on the compromise between computational efficiency and detection effectiveness, two multiresolution levels are generally sufficient for the defect-detection application as presented in this paper. The proposed method involving multidimensional wavelet features obtained from the two-level 2-D discrete wavelet transform (DWT), as applied to defect detection, can be outlined in the following steps.

Step 1) The $N \times N$ $(N > 200)$ image is raster scanned by 200×200 sliding windows, which is considered to save computation time.
Step 2) Each such window is transformed into the wavelet domain using the two-level 2-D DWT. As a result, the wavelet coefficients organized in seven channels (or bands) are obtained.
Step 3) The second subimage f_{LL}^2 is extracted from the seven bands, in which most of noise is removed.
Step 4) Binary conversion is carried out for the f_{LL}^2 subimage.

C. Automatic Detection of Defects

After the process of casting an image, we may gain the results that are shown in Fig. 8. The rest is to determine whether the casting contains a defect or not; if yes, what type (e.g., air hole or shrinkage) and grade is the defect? In this paper, we

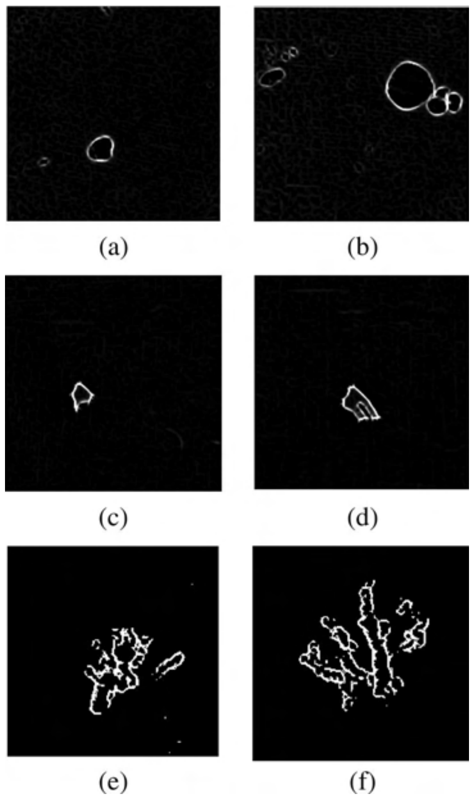


Fig. 4. Results of second-order derivative operations on Fig. 2(a) and (b).

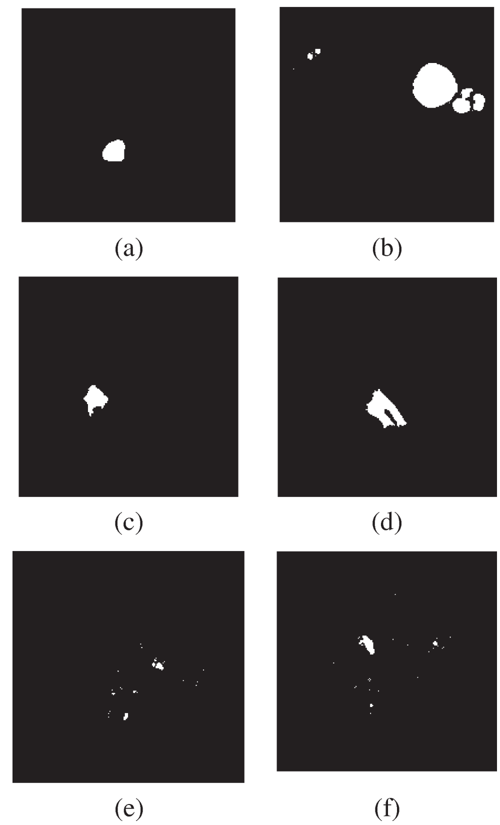


Fig. 5. Results of morphology operations on Fig. 3.

propose to examine the area of defect to determine whether the casting contains a defect. Once the area of a defect is less than 0. 05 mm^2, the casting contains a defect. At the same time, the size of the defect area can be used to determine the grade of the defects. The grade of the defect in casting is based on the utilization requirement of the casting; thus, this paper does not discuss this problem.

The distribution, perimeter, and numbers of defects can be used to determine the type of defect in the casting. Often, an air-hole defect is circular in shape, so the radius calculated by the defect area should approximate its circumference. If the difference between the two values is very close, it indicates that the defect is likely to be an air hole, although it is also possible to be a foreign object if the foreign object has the shape of a ball. Second, if the distribution of the defect in spatial space is sparse and the defects are not circular in shape, the defect is likely to be a shrinkage cavity.

IV. Results and Discussion

Casting defects shown in X-ray images are often difficult to detect automatically because the natures of different casting defects are very different; some defects are indicated by very thin lines or are not clear with poor contrast under X-ray. First, the second-order derivative and morphology approach is used to process the images in Fig. 2(a) and (b), and the results are shown in Figs. 4 and 5. Fig. 4 indicates that the second-order derivative operations can detect the edge of the defects. Morphology operations allow the defects in the images to be more clearly seen so that the method can easily discriminate the two types of defects: air holes and foreign objects. Unfortunately, the method has no effect on the third type of defects, namely, shrinkage cavities, as shown in Fig. 4(e) and (f). This is because the second-order derivative method smoothens the shape too much and tends to create closed loops of edges. To confirm the presence of shrinkage cavity, another method has to be employed.

Next, the row-by-row adaptive thresholding is used to process the images containing shrinkage cavities. If the calculated horizontal expected value of a pixel differs widely from the its actual gray level, this is evidence that a pixel represents a defect. Thus, this method can detect small defects, which do not differ significantly in gray level from the normal background. The results are shown in Fig. 6, which indicates that the method can effectively detect shrinkage cavities in the casting. However, the method is ineffective for the other internal defects in the casting (air holes and foreign objects), as shown in Fig. 6(a)–(d). One of the advantages of this method is relatively short processing time. However, some parameters (such as m and c) have to be determined empirically.

Finally, wavelet transforms are applied to process the images in Fig. 2. Fig. 7(a) shows the filtered image of Fig. 2(a)-(1). The subimage of Fig. 7(a) derived from the wavelet decomposition in level one is shown in Fig. 7(b). The subimage of Fig. 7(a) derived from the wavelet decomposition in level two is shown in Fig. 7(c). The final result based on binary conversion is shown in Fig. 7(d). Fig. 8 shows all the results derived from Fig. 2. These results show that the three types of defects in castings can effectively be detected by the wavelet approach.

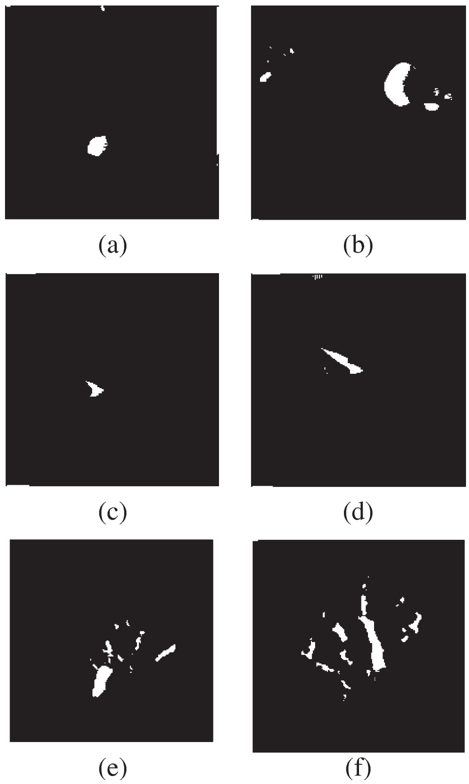


Fig. 6. Results of shrinkage-cavity defects by using row-by-row adaptive thresholding.

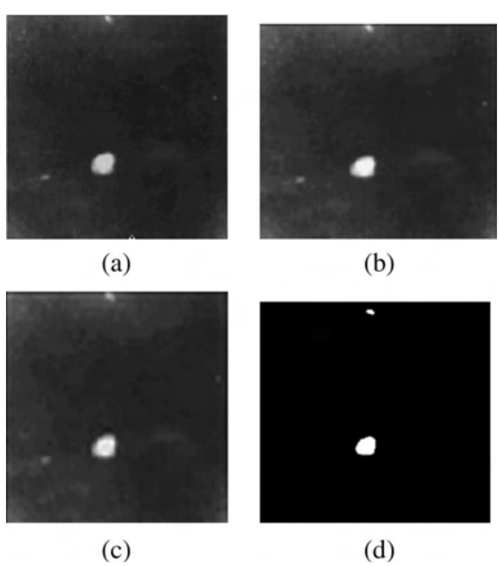


Fig. 7. (a) Filtered image of Fig. 2(a)-(1). (b) First subimage of Fig. 7(a) based on the wavelet in level one. (c) Second subimage of Fig. 7(a) based on the wavelet in level two. (d) Final result after binary conversion.

The efficiency of the wavelet approach in recognizing defects in castings, based on utilizing wavelet-domain information, is illustrated by comparing with the other two methods. Obviously, the defective areas are preserved and enhanced in the corresponding wavelet domains. From Fig. 8(a), it is found that the small defects can be detected for a size of the defect of less than 1 mm.

The three aforementioned methods have been tested on a set of castings with typical defect types (air holes, foreign

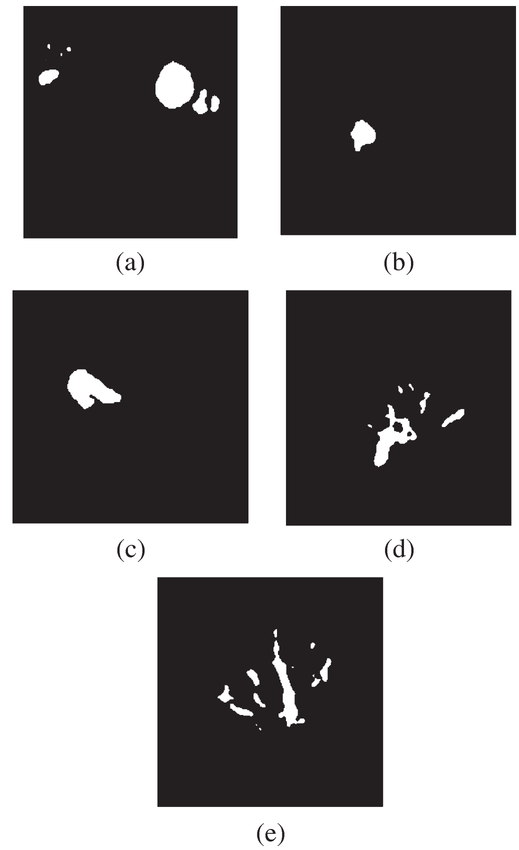


Fig. 8. (a) Final result of Fig. 2(a)-(2). (b) Final result of Fig. 2(b)-(1). (c) Final result of Fig. 2(b)-(2). (d) Final result of Fig. 2(c)-(1). (e) Final result of Fig. 2(c)-(2).

objects, and shrinkage cavities). A total of 21 defects have been selected, of which seven belong to the air-hole type (diameter ranges from 1 to 5 mm), seven belong to the foreign-object type (area ranges from 1 to 4×4 mm^2), and seven belong to the shrinkage-cavity type (width ranges from 0.5 to 6 mm). As shown in Table I, all of the defects can be automatically detected by applying wavelet transform and calculating the defects. The second-order derivative and morphology operations can successfully detect 13 defects only (six of the air-hole type and seven of the foreign-object type). The row-by-row adaptive thresholding can detect nine defects (one of the air-hole type, two of the foreign-object type, and six of the shrinkage-cavity type). The major advantages of the wavelet method can be summarized as follows. 1) This single technique can detect the three types of typical defects in castings. 2) It is sensitive to even small defects in castings with sizes of 1 mm or below. 3) No thresholding values or parameters have to be selected, and the procedure of its application is simple.

V. Conclusion and Future Work

The automation of defect detection for castings by X-ray inspection can overcome the difficulties encountered in conventional manual methods. This paper first addresses the typical defects found in castings and the X-ray inspection system. The second-order derivative and morphology operations, the row-by-row adaptive thresholding, and 2-D wavelet transform are

TABLE I
DETECTION RATE OF THREE METHODS

Methods	Air-hole	Foreign objective	Shrinkage
Wavelet technique	7/7	7/7	7/7
Second-order derivative and morphology operations	6/7	7/7	0/7
Row-by-row adaptive thresholding	1/7	2/7	6/7

methods proposed to process the images showing different defects of the castings. The test results show that the first method is only efficient to detect air-hole and foreign-inclusion defects; the second method is found to be suitable mainly for detecting shrinkage cavities. However, wavelet transform can effectively deal with the three defects types presented. Therefore, wavelet transform may be applied to detect automatically the internal defects of the castings based on X-ray inspection.

There are still problems associated with the application of wavelet transform to defect detection in castings. In this paper, the number of multiresolution levels must be manually predetermined for each image, although typically two levels are satisfactory in most cases. In the future, we will study how to select the number of multiresolution levels for the best enhancement of defects based on the gray-level variance and the energy in the subimages.

Typical inspection requirements include specifying defect types to be identified and applying different inspection criteria to a series of regions of interest (maximum number of defects, maximum length and width of defects, area, position and orientation of defects, total defect area, and defect region density).

How to design a classifier to identify the various defects will be the next important task to be tackled. Although the defect classification problem is outside the scope of this paper, the final aim of automatic checking of defects is to achieve high reliability, low cost, easy manipulation, portability, and real-time presentation of results for on-line application.

ACKNOWLEDGMENT

X. Li would like to thank the Alexander von Humboldt Foundation in Germany for providing the chance to write this paper.

REFERENCES

[1] D. Mery, R. da Silva, L. P. Caloba, and J. M. A. Rebello, "Pattern recognition in the automatic inspection of aluminium castings," *Insight*, vol. 45, no. 7, pp. 475–483, Jul. 2003.
[2] D. Mery and M. A. Berti, "Automatic detection of welding defects using texture features," *Insight*, vol. 45, no. 10, pp. 676–681, Oct. 2003.
[3] D. Hippe-Wallenwein, "Industrial X-ray 1895 until today," *NDT.net*, vol. 2, no. 1, 1997. [Online]. Available: http://www.ndt.net/article/hippe/hippe.htm
[4] D. Mery and D. Filbert, "Automated flaw detection in aluminum castings based on the tracking of potential defects in a radioscopic image sequence," *IEEE Trans. Robot. Autom.*, vol. 18, no. 6, pp. 890–901, Dec. 2002.
[5] D. Mery, "New approaches for defect recognition with X-ray testing," *Insight*, vol. 44, no. 10, pp. 614–615, 2002.
[6] F. Brant, "The use of X-ray inspection techniques to improve quality and reduce costs," *NDT.net*, vol. 5, no. 5, 2000. [Online]. Available: http://www.ndt.net/article/v05n05/brant/brant.htm
[7] W. Daum *et al.*, "Automatic recognition of weld defects in X-ray inspection," *Brit. J. Nondestruct. Testing*, vol. 29, no. 2, pp. 79–82, 1987.
[8] A. Gayer *et al.*, "Automatic recognition of welding defects in real-time radiography," *NDT Int.*, vol. 23, no. 3, pp. 131–136, Jun. 1990.
[9] J. Munro *et al.*, "Weld inspection by real time radioscopy," *Mater. Eval.*, vol. 45, no. 11, pp. 1303–1309, 1987.
[10] K. Inoue and M. Sakai, "Automation of inspection for weld," *Trans. Jpn. Welding Res. Inst.*, vol. 14, no. 1, pp. 35–44, 1985.
[11] H. Strecker, "A local feature method for the detection of flaws in automated X-ray inspection of castings," *Signal Process.*, vol. 5, no. 5, pp. 423–431, Sep. 1983.
[12] Y. Zheng and J. P. Basart, "Image analysis, feature extraction and various applied enhancement methods for NDE X-ray images," *Rev. Prog. QNDE*, vol. 7, pp. 813–820, 1988.
[13] V. Kaftandjian *et al.*, "Automatic inspection of aluminium ingots by digital radioscopy," in *Proc. 14th World Conf. Non-Destructive Testing*, New Delhi, India, 1996, pp. 1335–1338.
[14] A. Kehoe, "The detection and evaluation of defects in industrial images," Ph.D. dissertation, Univ. Surrey, Guildford, U.K., 1990.
[15] V. Lashkia, "Defect detection in X-ray images using fuzzy reasoning," *Image Vis. Comput.*, vol. 19, no. 5, pp. 261–269, Apr. 2001.
[16] V. Kaftandjian, O. Dupuis, D. Babot, and Y. M. Zhu, "Uncertainty modelling using Dempster–Shafer theory for improving detection of weld defects," *Pattern Recognit. Lett.*, vol. 24, no. 1–3, pp. 547–564, Jan. 2003.
[17] C. Jacobsen and U. Zscherpel, "Automated evaluation of digitized radiographs with neuronal methods," in *Proc. Int. Symp. Comput. Tomography Ind. Appl. and Image Process. Radiology*, Berlin, Germany, 1999, pp. 141–152.
[18] T. Someiji, T. Yoshimura, and N. Akiyama, "Development of automatic surface inspection system of casting," *J. Jpn. Soc. Pre. Eng.*, vol. 32, no. 4, pp. 278–283, 1998.
[19] Y. Okawa, "Automatic inspection of surface defects of cast metals," *Comput. Vis. Graph. Image Process.*, vol. 25, no. 1, pp. 89–94, 1984.
[20] A. Lee, "Diecasting defective detection by image processing," *Diecasting*, vol. 5, no. 102, pp. 1–3, 1995.
[21] T. Watanabe, "Ultrasonic nondestructive testing of FCD steering knuckle," *Elementary Forming Mater.*, vol. 9, no. 11, pp. 25–29, 1996.
[22] H. Boerner and H. Strecker, "Automated X-ray inspection of aluminum castings," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 10, no. 1, pp. 79–91, Jan. 1988.
[23] Z. Zhang and J. P. Basart, "Feature extraction and classification in automated inspection of NDE images," *Rev. Prog. QNDE*, vol. 14, pp. 741–746, 1995.
[24] K. R. Castleman, *Digital Image Processing*. Saddle River, NJ: Prentice-Hall, 1996.
[25] J. S. Lim, *Two-Dimensional Signal and Image Processing*. Englewood Cliffs, NJ: Prentice-Hall, 1990.
[26] J. C. Russ, *The Image Processing Handbook*, 3rd ed. Boca Raton, FL: CRC Press, Oct. 1998.
[27] S. Maede, H. Kubota, and H. Kakihira, "Optimum threshold generation for automated visual inspection of large scale integration wafer patterns," *Syst. Comput. Jpn.*, vol. 27, no. 11, pp. 74–86, 1996.
[28] J. Serra, *Image Analysis and Mathematical Morphology*. London, U.K.: Academic, 1982.
[29] J. S. L. Lee, R. M. Haralick, and L. G. Shapiro, "Morphological edge detection," *IEEE J. Robot. Autom.*, vol. RA-3, no. 2, pp. 142–155, Apr. 1987.
[30] D. T. Pham and R. J. Alcock, "Automatic detection of defects on birch wood boards," *J. Process Mech. Eng., IMechE*, vol. 210, no. 1, pp. 45–52, 1996.
[31] H. J. A. M. Heijmans, "Morphological image operators," in *Advances in Electronics and Electron Physics*. Boston, MA: Academic, 1994.
[32] P. Steffen, P. N. Heller, R. A. Gopinath, and C. S. Burrus, "Theory of regular M-band wavelets bases," *IEEE Trans. Signal Process.*, vol. 41, no. 12, pp. 3497–3510, Dec. 1993.
[33] D. Tsai and B. Hsiao, "Automatic surface inspection using wavelet reconstruction," *Pattern Recognit.*, vol. 34, no. 6, pp. 1285–1305, 2001.

Xiaoli Li received the B.S.E. and M.S.E. degrees from Kunming University of Science and Technology, Kunming, China, in 1992 and 1995, respectively, and the Ph.D. degree from Harbin Institute of Technology, Harbin, China, in 1997, all in mechanical engineering.

From April 1998 to October 2003, he was a Research Fellow with the Department of Manufacturing Engineering, City University of Hong Kong, Kowloon, Hong Kong and with the Alexander von Humboldt Foundation, Institute for Production Engineering and Machine Tools, Hannover University, Hannover, Germany, and a Postdoctoral Fellow with the Department of Automation and Computer-Aided Engineering, Chinese University of Hong Kong, Hong Kong. In 2002, he was appointed Professor at the Institute of Electrical Engineering, Yanshan University, Qinghuangdao, China. He is also currently with Cercia, School of Computer Science, University of Birmingham, Birmingham, U.K. He has published two books and 40 journal papers. His research interests include computational intelligence, signal processing and data analysis, monitoring, bio-signal analysis (EEG), and manufacturing systems.

S. K. Tso (SM'81) received the B.Sc.(Eng.) degree from the University of Hong Kong, Hong Kong, and the M.Sc. and Ph.D. degrees from the University of Birmingham, Birmingham, U.K., all in electrical and electronic engineering.

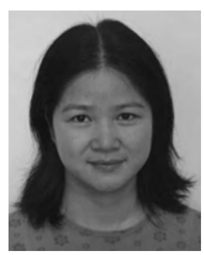
He has served for long periods at the University of Hong Kong and City University of Hong Kong, Kowloon, Hong Kong. Before retiring in 2004, he was a Professor of mechatronics and automation and the Director of Consortium for Intelligent Design, Automation, and Mechatronics, Department of Manufacturing Engineering and Engineering Management, City University of Hong Kong. He has carried out research in the broad field of industrial electronics, automation, and control, supervised numerous Ph.D., M.Phil., and M.Sc. students, and published more than 350 scientific papers. He has held visiting professorships at many universities including the University of Toronto, Toronto, ON, Canada, and the University of Waterloo, Waterloo, ON. He has also served as External Examiner for Ph.D. and M.Phil. theses submitted to universities in Australia, Singapore, Malaysia, and Hong Kong. He is an Honorary Professor at a number of universities in Hong Kong and abroad.

Dr. Tso has served as Chairman of the IEEE Hong Kong Section, Chairman of the Institution of Electrical Engineers (IEE) Hong Kong, and Chairman of the Control, Automation, and Instrumentation Division, Hong Kong Institution of Engineers (HKIE). He is a Fellow of the IEE and the HKIE.

Xin-Ping Guan (M'03–SM'04) received the B.S. degree in mathematics from Harbin Normal University, Harbin, China, in 1986, and the M.S. degree in applied mathematics and the Ph.D. degree in electrical engineering from Harbin Institute of Technology, Harbin, in 1991 and 1999, respectively.

He is currently a Professor and the Dean of the Institute of Electrical Engineering, Yanshan University, Qinhuangdao, China. He is also with the Center for Networking Control and Bioinformatics, Yanshan University. He has published more than 120 papers in mathematical and technical journals and conferences. As an investigator or co-investigator, he has finished more than 17 projects supported by the National Natural Science Foundation of China, the National Education Committee Foundation of China, and others. He is also a Reviewer of *Mathematics Review of America*. His research interests include functional differential and difference equations, robust control and intelligent control of time-delay systems, chaos control, and synchronization and congestion control of networks.

Dr. Guan is a member of the Council of Chinese Automation Committee and the Council of Chinese Artificial Intelligence Committee.



Qian Huang was born in Hunan, China. She received the M.S. degree in mechanical engineering and the Ph.D. degree in computer engineering from South China University of Technology, Guangzhou, China, in 1992 and 2005, respectively.

She held a visiting position in the Department of Manufacturing Engineering and Engineering Management, City University of Hong Kong, Kowloon, Hong Kong, from 1997 to 1998. She is currently an Associate Professor with the School of Electrical and Information Engineering, South China University of Technology. She is also a Fellow of the China Artificial Intelligence Academy, Guangzhou. Her research interests include computer vision, image processing, and industry detection.