NDT&E International 46 (2012) 14–21

Contents lists available at SciVerse ScienceDirect

NDT&E International

journal homepage: www.elsevier.com/locate/ndteint

Automatic weld defect detection based on potential defect tracking in real-time radiographic image sequence

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ARTICLE INFO

Article history:
Received 18 April 2011
Received in revised form
18 October 2011
Accepted 24 October 2011
Available online 6 November 2011

Keywords:
Non-destructive testing
Radiographic image sequence
Weld defect
Automatic detection
Hough transform

ABSTRACT

An effective and adaptive method is proposed to automatically detect weld defects using defect tracking in real-time radiographic image sequence of a moving weld. Firstly, a defect segmentation algorithm with low threshold is used to segment all of the potential weld defects in each image of the sequence. Then the modified Hough transform is employed to track the center of gravity of potential defects in image sequence, and the potential defects that cannot be tracked are eliminated as false defects. Experiment results show that the proposed method can detect weld defects with high certainty and avoid false alarms caused by the noise.

1. Introduction

Radiographic testing is one of the commonly used Non-destructive testing (NDT) methods for detecting weld defects [1]. The technique of radiographic testing with film is expensive and time-consuming. Therefore real-time radiographic imaging technique has been developed and applied. For example, it is often applied in real-time detection of long weld structures, such as weld pipe manufacturing in factory. The traditional interpretation of radiographs by artificial method is subjective, inconsistent, and easy to cause fatigue. In order to improve the automation level and avoid drawbacks of manual interpretation, the methods of automatic weld defects inspection from radiographic images have been extensively studied.

Researchers all over the world have studied and proposed many useful image processing methods for weld defects segmentation and recognition in radiographic image, such as background subtraction [2–4], gray-level profile analysis [5,6], mathematical morphology [7], watershed algorithm [8], fuzzy reasoning [9] and texture feature analysis [10]. However, these methods mainly focus on the digitized film image and utilize only the information in single image for weld defect detection. The main differences between defect detection with real-time radiography (on line detection) and defect detection with film (off line detection) are as follows: (1) in on line defect detection studied in our work the defect is detected in real-time when the weld is moving, while in off line defect detection, the defect is detected off line; Therefore on line defect detection requires a computationally fast and effective method; (2) the signal-to-noise ratio of real-time radiography is much lower than that of digitized film, which is a very challenging problem in automatic defects inspection with real-time radiography. The main task in on line automatic defect detection is now focused on segmentation and location of detects in weld [11], while the main task in off line defect detection is now focused on classification of different types of weld defects [12]. In real-time radiographic image sequence of a moving weld, it is not easy to distinguish the low contrast defect and the false defect caused by noise even by human inspection if using only one image. Consequently, the methods to detect defects using only one image each time cannot solve the conflict between detecting weld defects and avoiding false alarms in real-time automatic defect detection.

Currently, there are a few studies on defect automatic detection by utilizing the reappearance of defects in sequence of radiographic images to improve detection result. For instance, Mery and Filbert et al. [13] proposed an automated flaw detection method in aluminum castings based on the tracking of potential defects in a radioscopic image sequence, and Zhou and Du [14] presented an automated defect detection technique based on multiple radiographic images to detect the defect of blade of aviation engine. In both methods a sequence of radiographic

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doi:10.1016/j.ndteint.2011.10.008

images are captured from different known positions of the work piece, and then the potential defect is matched and tracked from image to image by some constraints such as epipolar constraint. Nevertheless, the two methods have the requirements that the imaging system needs to be calibrated and the position of the object must be known, and therefore they are not applicable to real-time radiographic image sequence of weld whose moving speed is unknown. Du et al. [15] proposed a method of registration of image sequence based on detection of weld direction and phase correlation algorithm before defect detection, which gives a foundation of utilizing information among images of a sequence. However, the registration of image sequence is usually time consuming.

Automatic detection of weld defect in real-time radiographic image usually consists of two steps: (1) weld extraction and (2) defect segmentation. We present a novel idea as the third step for weld defect automatic detection. The idea is to distinguish real defects from false defects caused by noise by tracking the relative centers of mass of potential defects in sequence of images. The rationale is that the real defect will appear with regular track in sequence of images, while the false defects resulting from noise will appear randomly. The method of weld extraction has been proposed in our another paper [16], approach of segmentation of potential defect will be proposed briefly in Section 2, and the idea and algorithm of potential defect tracking will be presented in detail in Section 3. In Section 4, the real-time X-ray imaging system for experiments and corresponding experiments will be described to prove the effectiveness of proposed method, and finally conclusions are given.

2. Segmentation of potential defect

2.1. Noise reduction

The object of noise reduction is to filter the interference and make the target features more prominent. The noise in radiographic weld images is usually Gauss noise and salt and pepper noise. In this work, a 3×3 median filter template and a 5×5 average filter template are used to filter the image.

2.2. Background subtraction and gray-level profile analysis

Background subtraction is one of the usual methods in weld defects segmentation in radiographic images [2–4]. The main steps of background subtraction algorithm used in this work are as follows.

(1) Estimate the background image by using the 11×11 average filter template to the image.
(2) Subtract the background image from the original one to obtain residual image.
(3) Obtain the binary image by applying an appropriate threshold to the residual image.

The gray-level profile analysis is also applied to segment the weld defect in this work. The gray-level profile across the weld is analyzed column by column in this method, and the defect region is segmented column by column. Denote the gray-level profile of current column to be processed by $f_j(i)$, the main steps of gray-level profile analysis are as follows.

(1) Calculate the first-order derivative $f_j'(i)$ and second-order derivative $f_j''(i)$ of $f_j(i)$.
(2) Search all the points i_0 in weld region which satisfy the conditions $f_j'(i_0-1)>0$ and $f_j'(i_0+1)<0$, and then search the first two points i_1 and i_2 separately from i_0 to each side of i_0 which satisfy $f_j''(i_1-1)>0$ and $f_j''(i_2+1)>0$. If both $f_j'(i_1)$ and $f_j'(i_2)$ are greater than a pre-defined first-order difference threshold, then the interval $[i_1,i_2]$ is considered as the defect region in the current column, and denoted by one in binary image.

After all the columns are analyzed through the above steps, the binary image of defect segmentation is obtained by gray-level profile analysis.

The background subtraction algorithm used in this work can detect defect effectively and obtain accurate defect shape, but may result in many false alarms around weld edges because of inaccurate estimation of background. As to the gray-level analysis, it is sensitive to noise instead of weld edges, and the shape of the segmented defect is not accurate. Consequently, integration of the two methods will improve the defect segmentation result and avoid a large proportion of false alarms around weld edges. In this work, low thresholds are used in both methods to ensure that all the real weld defects are segmented in each image of the sequence, and then the intersection set of binary images obtained by two methods is considered as the segmentation result of potential weld defects.

2.3. Potential defect labeling and parameters calculating

After the binary image of potential weld defects is obtained by the approach proposed above, the 2×2 template close and open morphology filters are applied to the binary image successively, and then the potential defects can be labeled with different labels by connected-component labeling algorithm. Denote the image size to be processed by $Height\times Width$, and the detected weld upper and lower edges by $mUpEdge(j)$ and $mDownEdge(j)(j=1,2,\ldots,Width)$ separately. Then $mWeldMid(j)=(mUpEdge(j)+mDownEdge(j))/2(j=1,2,\ldots,Width)$ is the center of the weld. Suppose that the residual image obtained by background subtraction described in Section 2.2 is $mSub(i,j)$, and denote the pixel number of a segmented defect as the defect area by $mArea$. Use Eqs. (1)–(3) to calculate the relative coordinates (X_q,Y_q) of the center of gravity of the potential defect

$$Y_q=round\left(\frac{\mathrm{Sum}((j-mWeldMid(j))*mSub(i,j))}{\mathrm{Sum}(mSub(i,j))}\right)\quad(\text{for all Pixel}(i,j)\text{ labeled }q)\tag{1}$$

If the weld is moving towards right, then calculate X_q by

$$X_q=round\left(\frac{\mathrm{Sum}(i*mSub(i,j))}{\mathrm{Sum}(mSub(i,j))}\right)\quad(\text{for all Pixel}(i,j)\text{ labeled }q)\tag{2}$$

If the weld is moving towards left, then calculate X_q by

$$X_q=Width+1-round\left(\frac{\mathrm{Sum}(i*mSub(i,j))}{\mathrm{Sum}(mSub(i,j))}\right)\quad(\text{for all Pixel}(i,j)\text{ labeled }q)\tag{3}$$

By applying a small defect area threshold, the small false alarms caused by noise are eliminated.

3. Potential defects tracking in image sequence

3.1. Idea of potential defect tracking in image sequence

A sequence of images is shown in Fig. 1a. The images are parts of the real-time X-ray images which are obtained in equal time intervals when the weld with a defect is moving in close to a constant speed. The potential defects segmentation results of the images are shown in Fig. 1b, where the white districts represent the segmented potential defects. It can be observed that the real defect appears regularly and the track forms a line, while the