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Detection of line weld defects based on multiple thresholds and support vector machine

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ABSTRACT

Because X-ray images of weld contain uncertain noise and also the defects inside them have low contrast to their background, it is difficult to detect weld defects of X-ray images. The goal of this paper is to locate and segment the line defects in X-ray images. Firstly, we present an approach to extract features of X-ray images with multiple thresholds. Then, use the support vector machine (SVM) technique to classify the defect and non-defect features to obtain a coarse defect region. Furthermore, perform the Hough transform to remove the noisy pixels in the coarse defect region. Then the defect is located and segmented. The experimental results show that the proposed approach is effective and feasible to segment and locate defects in noisy and low contrasted X-ray images of weld.

1. Introduction

Weld defect detection from X-ray images is important in industrial manufacturing. However, human inspectors do not show great advantages in detecting weld defects both in quality and in quantity. As a matter of fact, this task is tedious and fatigue for human inspectors. Therefore, to automate the detection process is necessary to reduce the manpower cost and to improve the detection objectivity. Developments in image processing, computer vision, artificial intelligence and other related fields have significantly improved the capability of visual inspection techniques [1]. Various algorithms were applied in weld defect detection for X-ray images. Classic automatic defect detection includes two steps: (1) image preprocessing and (2) feature extraction and decision-making. Research groups all over the world have examined a number of methods on both steps. The image preprocessing step reduces the unwanted information and enhances the desired information about defects. Popular image preprocessing includes noise removing [2], image enhancement [3], edge detection [4], image segmentation [5], morphological processing [6] and so on. The next step is to extract the feature from the processed image and process it with decision methods. The following features are of most interests in the processed area, shape feature [7,8], texture feature [9] and transformed feature. With the extracted feature, the defect can be detected automatically by decision solutions, such as distance function, Bayesian decision, neural networks [7,10,11], support vector machine (SVM) [12,13], fuzzy function [14] and so on. Generally, there are five major types of weld defects: incomplete fusion, incomplete penetration, slag inclusion, gas cavity and crack. They can be recognized in the form of gap, crack or pore and cavity. According to GB 3323-87 standard, gap and crack detections are more important than pore and cavity for steel pipe manufacturing. Actually, it is difficult to detect line defects (in the shape of gap and crack) due to the fact that the X-ray images of weld contain much uncertain noise and the defect has low contrast to its background. This paper focuses on detecting the line defects in X-ray images of weld, where multiple thresholds are employed to extract the image features. Then the image features are input into an SVM to obtain a coarse defect region. With Hough transform, the segmental defect can be extracted from the coarse region.

2. Structure of the detection system

The system consists of conversion part, processing part and serial communication part as shown in Fig. 1. The conversion part consists of X-ray source, weld seam, transmission vehicle, intensifier and CCD camera. The function of this part is to make the conversion from X-ray to visible light. Firstly, X-ray is transferred into visual light through light intensifier. Then the CCD camera transfers the light signal into electric signal and sends it to the processing part. The processing part consists of monitor, image grabber, computer and computer screen. In this part, the

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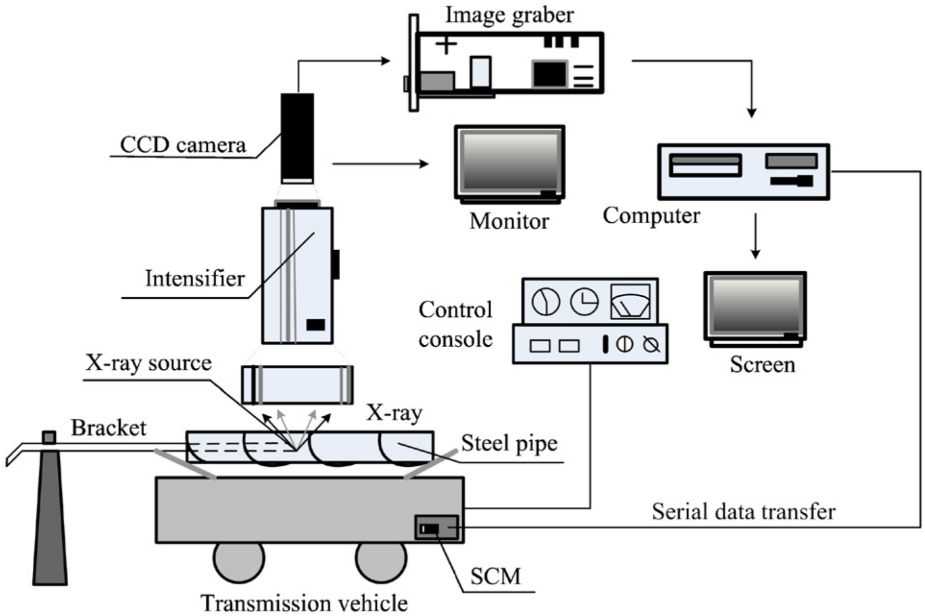

Fig. 1. The structure of detection system.

electric signal is acquired by image grabber, and at the same time it is also displayed on the monitor. The digital image is sent into the computer and will be analyzed using the proposed algorithm in this paper. The result will be displayed on computer screen in real-time and stored in computer for future check or test. The above imaging system has already been setup. The quality of imaging cannot be changed if we do not replace the hardware. Our method is to find an effective arithmetic that can detect the defects reliably.

3. Feature analysis and extraction

Considering the high level of uncertain noise and low object-background contrast of X-ray images, we implement a novel approach of feature extraction.

As an example, Fig. 2(a) is an X-ray image of a steel pipe. There are three main areas: base metal area, weld area and lead plate area. As shown in the picture, the defect only exists in the weld area. Firstly, we extract the weld area from the background using the adaptive segmentation algorithm [14]. The result is shown in Fig. 2(b). After the weld area is extracted from the image, the next step is to get the defect features from the extracted weld area. Because the weld area contains much noise and the contrast level of the defect to its background is low, it is not effective to obtain the features of defects from the weld area by using traditional approaches, such as threshold segmentation [2,5,15], edge detection [6,16,17] and transform technique [4,18,19]. Our approach is to get the features of defects from the extracted weld area by multiple thresholds, and the detail is described as follows.

As shown in Fig. 3, the extracted weld area is denoted as $I_{M\times N}(m,n)$ $(m=1,\ldots,M,\ N=1,\ldots,N)$. M and N are the width and height of the extracted weld area, respectively, and in this paper $M\times N$ is 460×90. With the size of 45×30 pixel, we make a window that will slide from the left-top to the right-bottom of $I_{M\times N}(m,n)$ with the interval of 2 pixel. Then the parts within the sliding window will be denoted as a series of blocks of $I_{M\times N}(m,n)$, as shown in Fig. 3. Fig. 3(a) shows the location of the first block. Fig. 3(b) shows the second block and the ith block is shown in Fig. 3(c). The defect may exist in some of the blocks.

After getting a series of blocks from the weld area, we perform following steps in each block from which the features can be extracted, and the simple illustration of feature extraction is shown in Fig. 4.

We first arrange the brightness values of all pixels into an ordered vector, for example, $G=[g_1,g_2,\ldots g_i,\ldots g_L](g_1>g_2>\ldots>g_L)$ $(1\leqslant i\leqslant L)$, where L is the number of brightness levels and g_i denotes the particular brightness value. Then, select a subset $G_s=[g_3,\ldots,g_{20}]$ from G, and every element of G_s is, respectively, adopted as the threshold to segment the block. The reasons of selecting g_3–g_{20} are as follows: (1) Because the pixels of the defect are brighter than those of the background, we select the greater part of G as the thresholds. (2) As g_1 and g_2 only filter out limited isolated points that represent irregular features in the binary image, they are removed from the further process. Then, we can get the first binary image, which is denoted $B_1(p,q)$ $(p=0,\ldots,44,\ q=0,\ldots,29)$ by segmenting the block with the threshold g_3. If the brightness value in the block is greater than g_3, the value of $B_1(p,q)$ is assigned 1. Otherwise, it is assigned 0. Using the same method with the thresholds g_4–g_{20}, we can totally get 18 binary images from a block and every binary image is denoted $B_i(p,q)$. Fig. 5 shows two blocks and their binary images. In Fig. 5(a) containing the defect, there can be found a similar pattern in the binary images. On the contrast, in Fig. 5(b) not containing the defect, there is no pattern found in the binary images. That is to say, in the binary images segmented from the blocks containing defects, most pixels with value 1 are distributed along the defects, while those from the blocks not containing defects are distributed at random (see Fig. 5). Furthermore, the above characteristics are achieved from a number of X-ray images of steel pipes, not from some particular areas. From the binary images, we can deeply consider the features that can distinguish blocks containing defects from those not containing defects. The detail is described as following: in every binary image $B_i(p,q)$ as shown in Fig. 6, we calculate the average distance D_i $(i=1,2,\ldots,18)$ between every pixel and the central horizontal axis of $B_i(p,q)$:

$$D_i=\frac{1}{T_i}\sum_{p=0}^{44}\sum_{q=0}^{29}B_i(p,q)\times|q-14.5| \tag{1}$$

where T_i is the number of pixels with the value of 1 in the binary image $B_i(p,q)$, and $|q-14.5|$ indicates the distance between