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Accurate defect detection via sparsity reconstruction for weld radiographs

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A R T I C L E I N F O

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A B S T R A C T

Detecting defects in weld radiographs is an important research topic in the field of industrial non-destructive testing. Many computer-aided detection techniques have been designed for detecting defects. However, these techniques are mainly used to detect specific defective types. They cannot be applied to detect diverse types of defects, which is a difficult task because the number and types of defects in weld radiographs are generally unknown in advance, and different defects may exhibit different visual properties in shapes, sizes, textures, contrasts and positions. Inspired by the experienced workers' visual inspection mechanism, this paper develops a novel framework to detect diverse types of defects from X-ray images. In the framework, a large number of normal X-ray images are firstly collected to serve as "workers' experience" and guide the defect detection. Then, a dictionary is learned from the collected normal set. It can selectively reconstruct the background and the weld region of a test image while suppressing defective regions via sparsity reconstruction. By computing the difference image between the test image and its reconstructed image, flaws are well highlighted as the reconstruction residuals and separated from the difference image. Extensive experiments have shown that the proposed technique detects diverse defects more accurately compared with the state-of-the-art methods.

1. Introduction

Welding defects directly influence the mechanical properties of welded steel pipes and shorten their service life, and may even lead to a catastrophic accident [1]. Radiographic testing (RT) is a popular non-destructive testing (NDT) technique for detecting welding defects. It utilizes the properties of X-rays, which could pass through metal and other materials opaque to the ordinary light, to produce photographic records by the transmitted radiant energy [2]. Because the abilities of different materials to absorb X-rays are different, the penetrated X-rays show variations in intensity on the X-ray images (radiographs), which may provide a method to examine the internal structure of a welded steel pipe.

Inspection of the weld quality can improve the qualification ratio of welded steel pipes and avoid major accidents. For this purpose, weld defect screening is widely used in the field of non-destructive testing by manually inspecting radiographic images. Its main task is to detect all possible defective regions from radiographic images. However, this is a subjective, complex and labor-intensive task for workers. Inexperienced workers may miss some low-contrast defects or mistakenly identify some normal regions as defects. Even experienced ones sometimes make similar mistakes after long hours of work. In order to overcome such drawbacks from human factors, this paper proposes an automatic computer-aided radiogram interpretation technique to detect diverse types of defects from weld radiographs.

The X-ray images of thick steel pipes may contain diverse types of weld defects, which show different visual properties in textures, positions, sizes, shapes and contrasts, as shown in Fig. 1. Additionally, the number and types of defects are generally unknown in advance. Furthermore, in these X-ray images, the grayscale distribution is uneven and the signal-to-noise ratio is low. These factors make it a challenging task to accurately detect different types of defects from different X-ray images.

In the past two decades, many algorithms [1–9] have been proposed to detect defects from industrial images automatically. Current approaches for detecting detects can be generally classified as: machine learning methods based on defect training patches, feature-designing-based methods, and background subtraction methods. In the first class [1,3,6,7], features of defects are specified artificially or learned automatically, defect regions and non-defective ones are collected, and a

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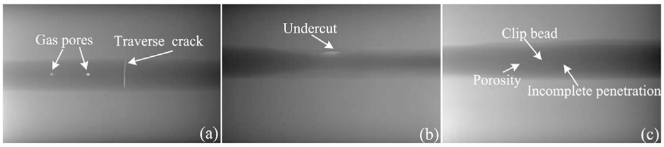

Fig. 1. Different X-ray images may contain diverse types of defects in (a)–(c). The defects exhibit diverse properties in shapes, sizes, contrasts, textures, and positions.

classifier is learned from the training set by machine learning methods. By the classifier, the specific types of defects can be detected. For the second class [4,5], similar important features of a specific type of defects are also artificially selected, and these defects of interest are detected from industrial images by a feature matching algorithm. The first two methods are only designed to detect a given type or few types of defects, but cannot be applied for these defect types that have not been trained, especially for those which are new or unseen before or whose features are different from the features specified or learned in advance. In the third class [2,8,9], some researchers use background subtraction techniques to detect various defects from radiographic images. In Ref. [2], each weld X-ray image is imported in TableCurve from SPSS and its background model is constructed by a quadratic polynomial model. Defects are detected from the residual image between the estimated background and the original image. Since radiographic images of thick steel pipes contain many uncertain noises, this method is difficult to accurately estimate the background and some normal personalized areas may be mistakenly identified as defective regions. In Ref. [8], a low-pass filter is utilized to eliminate the defects while keeping the background variations in the original X-ray images. However, the method relies heavily on the choice of the filter size. When the filter size is too small, the defect may not be filtered out, resulting in defect detection failure. On the other hand, when the filter size is too large, the accuracy of the estimated background is low and the defective regions cannot be well separated from the residual image. In Ref. [9], the weld background image is computed by using an 11×11 average filter template to the original image. This method cannot adapt to individual differences of normal regions in different test X-ray images, and some normal personalized areas may be mistakenly detected as defects because of inaccurate estimation of the background.

Since existing defect detection techniques cannot well detect diverse types of defects, this motivates us to develop new ways to detect diverse defects from X-ray images. It is known that an experienced worker can visually detect all defective regions from different X-ray images, no matter whether these defective regions have greatly different features or are new types (or never seen before). We aim to develop a novel technique to detect diverse types of flaws from X-ray images by learning the detection experience of experienced workers.

We have communicated with some well-trained workers, and try to understand how an experienced worker visually detects various defective areas from an X-ray image. We find that a long-time training is important for an inspector. In the training procedure, they read and learn many normal X-ray images, and these normal images are served as their experience used in detecting various flaws. When they read a target X-ray image, they compare implicitly the target image with a set of known normal similar images they have seen and consider a region as a defective region if there is no similar region found in the normal set. Inspired by the workers' visual inspection mechanism, a large set of normal radiographic images are collected and regarded as the workers' experience in detecting diverse types of defects. Then, every normal image in the collected normal set is preprocessed so as to normalize them in size and grayscale. A dictionary is learned from the preprocessed normal set. It can selectively reconstruct the normal background and the weld region of a test image while suppressing defective regions using sparse reconstruction. By computing the difference image between the test image and its reconstructed image, diverse defects are accurately detected. Since the proposed algorithm can accurately reconstruct the weld region and the background, the false positives caused by normal personalized areas can be reduced effectively. Extensive experiments have shown that the proposed technique can more accurately detect diverse defects from X-ray images compared with state-of-the-art methods. This is a new way for defect detection, which is based on experience learned from normal X-ray images rather than the features of diverse defects.

The rest of this paper is organized as follows. In Section 2, we introduce the proposed method in detail. Section 3 presents the experimental results and compares with related methods. Section 4 discusses the influence of some factors on the algorithm and Section 5 draws a conclusion.

2. Methodology

In this section, we first describe the problem of detecting diverse defects from X-ray images, then, introduce the basic idea to solve the problem. Finally, we propose a computational framework to detect different types of defects based on a dictionary learning and sparse reconstruction technique.

2.1. Basic ideas for detecting diverse defects

In this part, a mathematical model of detecting diverse defects from weld radiographs is built. Based on the basic imaging principle of the X-ray image, an X-ray image with defective regions is formed by adding the logarithms of different parts, such as the background, the weld and the defect. In this paper, however, we will understand the X-ray image from a different point of view. We think that a defective image with the size of $m \times n$ (denoted by I) can be regarded as the superposition (not adding) of defective regions (denoted by I_D) onto a normal image (denoted by I_{BW}), as illustrated in Fig. 2. We use the following equation to describe the defective image:

$$I = I_D \oplus I_{BW} \tag{1}$$

where $\oplus$ denotes the superposition (not adding) of I_D onto I_{BW}. The superposition and addition are two different concepts. The superposition of the defective regions I_D onto the normal image I_{BW} means that, the regions I_D directly replace the corresponding regions in I_{BW}, rather than compute the gray sum of the two corresponding regions. If we could well reconstruct the normal image I_{BW} from the defective image, then defective regions I_D would be recognized as those regions that have large reconstruction errors. The analysis above suggests that the detection problem of diverse defects from I boils down to the estimation problem of its normal image I_{BW}. In fact, it is difficult to estimate I_{BW} from I directly. Therefore, in this paper, we will develop a feasible technique to compute I_{BW}.

In Section 1, we have discussed the well-trained inspectors' visual inspection mechanism. When experienced workers read a test X-ray image, they actually detect diverse defects by implicitly comparing the test image with a set of normal similar images. Inspired by the observation, we collect 500 normal weld radiographs to serve as the "inspectors' experience", and estimate I_{BW} from I under the guidance of such experience. The set of normal X-ray images is denoted as Φ.

Basically, this paper intends to detect defects by comparing I and the normal images in Φ. In order to facilitate the comparison between the test image I and each normal image in Φ, each image is normalized in size and

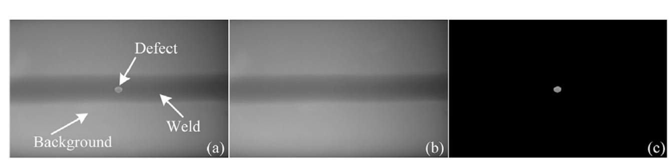

Fig. 2. A defective X-ray image can be regarded as the superposition of defective regions onto a normal image. (a) A defective X-ray image I. (b) The normal image I_{BW}. (c) Defective regions I_D.