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Context-Based Image Segmentation of Radiography

[1]W. Al-Hameed, [2]P.D. Picton, [3]Y. Mayali

[1]*Computer Science, University of Babylon, Iraq.*
[2]*School of Science & Technology,The University of Northampton,United Kingdom*
[3]*Faculty of mathematics & Computer Science,University of Kufa, Iraq.*

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ABSTRACT

In radiographic images, many researchers have used conventional image processing techniques to detect and segment any defects, which could include cracks, porosity or inclusions. Usually, these methods do not take into account the contextual knowledge that is used by the experienced radiographer, and instead use standard image processing techniques. In this research, knowledge about the defects and the images are used to develop a much simpler image processing technique.

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INTRODUCTION

One of the major areas of non-destructive testing is the inspection of welds, particularly in areas such as the oil and gas industry where pipelines contain thousands of welds. The inspection can take many forms, such as ultrasonic inspection, the use of eddy-current probes, and radiography, which could be x-ray or gamma ray. In the the case of radiography, the data that is produced is in the form of images, and the role of the NDT technician is to inspect the images (on film or digitally) to detect the existence of any flaws, and to assess their size. The ability of humans to detect the defects may be effected by the lighting, or due to a low level expertise which can give different interpretations of the same defect In an attempt to automate the process, previous research (W. Al-Hameed, Y. Mayali, P. Picton, 1-4, July 2013, X. Wang and B.S. Wong 2005, R. Silva and D. Mery, 2007, N. Nacereddine, M. Zelmat, S.S. Belaïfaand, M. Tridi, 2005) has used a variety of image processing techniques, some of which rely on statistical data to find local thresholds. These image processing methods have been developed to work on general purpose images, and do not take into account the specific knowledge that an experienced operator would know when analysisng images from radiography.

2. Defects in Welds:

The sort of defects that can be found in welds consist of cracks, trapped bubbles, cavities, and inclusions. Figure 1 shows some typical examples. Typically the aim of a radiograph is to get a good even contrast, so that defects that are large enough to be of concern will show up, usually as darker regions in the image. Since much of the image will not contain any defects, it is wasteful to have to apply complex image processing algorithms to the whole image. Therefore, a typical approach to this problem is to carry out a number of stages.

The first stage would be to quickly scan the image to find if there any areas that contain potential flaws. This would define “regions of interest” in which a flaw may exist. The second stage would be to isolate the flaw, and to identify all of the pixels that make up the image of a flaw. The third stage is usually feature extraction in which certain parameters of the flaw are extracted, in preparation for the final stage which is the identification and possibly measurement of the flaw. This paper is concerned with Stage 2 which is the identification of the pixels that belong to the image of the flaw.

Methodology:

Previous research by the authors has shown that one way of detecting regions of interest in a radiographic image is by edge detection, using a Sobel or Canny edge detector (S.S. Al-Amri, N.V. Kalyankar and S.D. Khamitkar, 2010). Regions in which rapid changes in intensity occur will be identified as regions of interest, and an area around that region defined. That is the starting point for the work reported in this paper.

Corresponding Author: W. Al-Hameed, Computer Science, University of Babylon, IRAN,

Australian Journal of Basic and Applied Sciences, 8(4) Special 2014, Pages: 24-28

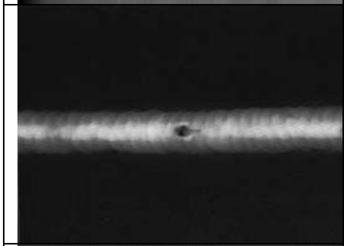
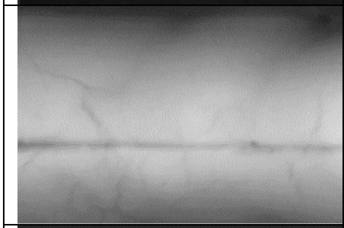
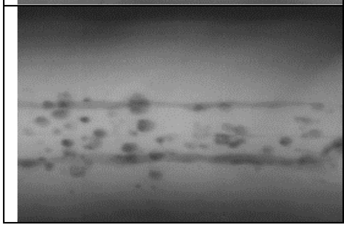
	**Elongated cavity** - large, non-spherical cavity with its major dimension approximately parallel to the axis of the weld
	**Burn-Through** - produced by the excessive heat of the weld metal when penetration welding zone which leads to the emergence of areas burned in the form of dark spots
	**Longitudinal crack** - crack essentially parallel to the axis of the weld
	**Slag inclusions** - nonmetallic solid material entrapped in weld metal or between weld and base metal.

Fig. 1: Examples of flaws in welds and their radiographs.

The aim in Stage 2 is to identify all, or as many, of the pixels that belong to the flaw. As already mentioned, any flaws in an image tend to be darker than the rest of the image. The first assumption would therefore be that a simple threshold would easily detect the flaw. The issue here is that of choosing the appropriate value of the threshold.

One option is to find a value of the threshold based on global information i.e. statistical information about the whole image. However, it is often the case that there is some local variation in the gray levels of the image because, for example, the image is of a pipe, in which case the object being tested curves away from the source of radiation, and is therefore darker at the edges. A threshold that is therefore able to pick out the flaw in one part of the image may also then pick out areas in other parts of the image where there are no flaws.

In this work use is made of the contect of the image, knowing that there is a difference in the statistical variation in the horizontal direction and in the vertical direction. Because of the way that these images are taken, there tends to be a farly constant gray level value in the horizontal direction, and a gradient from dark to light and then dark again in the vertical direction. Over the whole image there will be a statistical variation due to noise, which is assumed to be Gaussian and that this level of noise does not vary across the image.

This is illustrated in Fig.2a), where an image containing a flaw is shown. Fig.2b) shows two vertical cross sections, the first through part of the image where there is no flaw, and the second through part of the image containing the flaw. In the first it is fairly clear that the profile is a curve which has a low value at each end, and a maximum in the middle. Finally Fig. 2c) shows horizontal profiles, firstly through part of the image where there is no flaw and secondly through the flaw. In the first it can be seen that the gray level is farly constant (around 215) and that there is Gaussian noise. In the second profile the significant dip can be seen where the profile passes through the flaw.

Statistical Threshold:

Assuming that the noise throughout the image is Gaussian, then the distribution of the pixels would be expected to be a normal distribution, centred on a mean value and with 95% of the gray levels falling within ±2 standard deviations of the mean. Therefore, if the threshold is set to 2 x standard deviation below the mean, the flaw should be segmented, plus a small number of individual pixels.

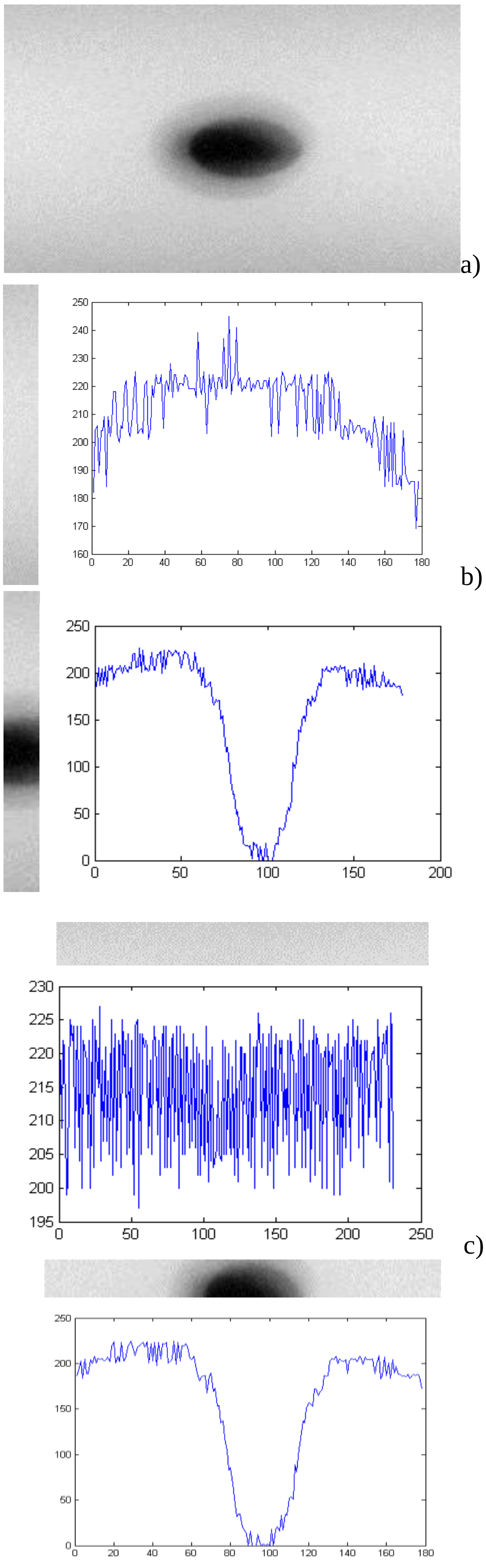


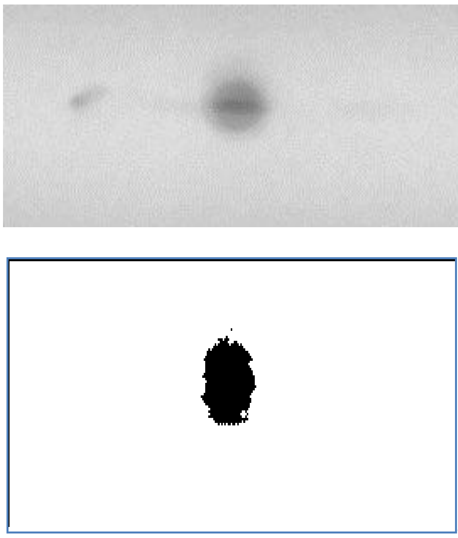
Fig. 2: a) Examples image containing flaw; b) vertical profiles c) horizontal profiles.

The mean and standard deviation values used in the segmentation are calculated using neighbouring regions to the regions of interest. These neighbouring regions have no flaws, and therefore give the mean and standard deviation of the image background. When the row means in the neighbouring area is found, the result is a similar profile to Fig. 2b). Then, if a pixel value is less than 2 times the standard deviation below the mean value of the row, it is catagorized as belonging to the flaw.

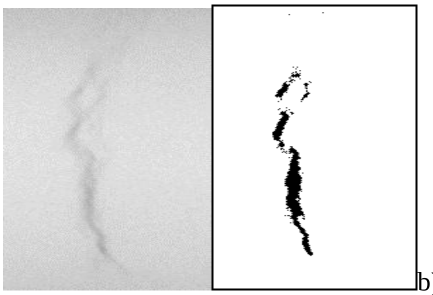
Australian Journal of Basic and Applied Sciences, 8(4) Special 2014, Pages: 24-28

RESULT AND DISCUSSION

Previous research (W. Al-Hameed, Y. Mayali, P. Picton, 1-4, July 2013, X. Wang and B.S. Wong 2005, R. Silva and D. Mery, 2007, N. Nacereddine, M. Zelmat, S.S. Belaïfaand, M. Tridi, 2005) has generally used far more complex image processing methods. Although these methods produce good results for many of the flaws, they generally are poor at detecting fine cracks. Fig.3 shows the results obtained using the method described in this paper. The first image shows that the method is good at detecting some of the easier flaws such as porosity. The second example shows how successful the method is at detecting the more difficult case of fine cracks. One additional feature was added, which was to remove any pixel which was classified as flaw, but which was an isolated pixel i.e. none of its eight neighbouring pixels were classified as flaws.



a)



b)

Fig. 3: a) Examples image containing a porosity; b)fine vertical cracks.

It can be seen that the flaws were well segmented and no other pixels were wrongly classified.

Future Work:

Having successfully segmented the flaw from the rest of the image, the next step is feature extraction and then classification. In order to achieve a good classification it is imperative that the segmentation contains as much of the flaw as possible, and that pixels wrongly attributed to the flaw are minimised. The algorithm presented in this paper appears to achieve this and has been successfully applied to a range of radiographic images. The features extracted are statistical, and include averages, moments, aspect ratios etc (I. Valavanis, D. Kosmopoulos, 2010). Once extracted the features are then fed into a linear support vector machine (LSVM) (T.Y. Lim, M.M. Ratnam and M.A. Khalid, March 2007, X. Wang, S. Wong and C.S. Tan, 2010) for training and then testing. So far, the success rate in classification has been as high as 82% correct. However, the aim of this research is to achieve over 90% correct classification, so there is still more work to be done.

Conclusion:

HThe main approach to identifying the pixels belonging to the image of a flaw is to use some form of thresholding. The selction of an appropriate threshold is problematic. In this poaper the approch has been to use the knowledge of the nature of radiographs to use a threshold based on the mean of the row of pixels, and the overall standard deviation. This has proven to be very successful, despite its simplicity, and is therefore a significant step in the direction of automating defect classification in weld radiography.

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