Submitted December 2006

The State of the Art of Weld Seam Radiographic Testing: Part II, Pattern Recognition

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ABSTRACT

Over the last 30 years, there has been a large amount of research attempting to develop an automatic (or semiautomatic) system for the detection and classification of weld discontinuities in continuous welds examined by radiography. There are basically two large types of research areas in this field: image processing, which consists in improving the quality of radiographic images and segmenting regions of interest in the images, and pattern recognition, which aims at detecting and classifying the discontinuities segmented in the images. Because of the complexity of the problem of detecting weld discontinuities, a large number of techniques have been investigated in these areas. This paper represents a state of the art report on weld testing and is divided into the two parts mentioned above: image processing and pattern recognition. The techniques presented are compared at each basic step of the development of the system for the identification of discontinuities in continuous welds. The first part of this paper (included in the June issue of this journal) dealt with image processing. This part deals with pattern recognition.

Keywords: *weld discontinuities, nondestructive testing, radiography, automatic weld testing, image analysis, pattern recognition.*

INTRODUCTION

Part I of this paper described almost all of the references dealing with image processing of weld radiographs. In this second part, we will discuss the main references on the classification of weld discontinuities in digitized radiographs in such a way as to make comparisons between the techniques used and the results obtained by the authors. Finally, a detailed table is presented with a summary of the content of both articles.

PATTERN RECOGNITION IN THE DETECTION AND CLASSIFICATION OF WELD DISCONTINUITIES

The second, but equally important, part of a system for the identification and classification of welding discontinuities using radiographs includes a number of pattern recognition techniques such as statistical classifiers, neuronal networks and fuzzy logic (Anouncia and Saravanan, 2006; Duda et al., 2002). The applications, which will be described below, use both the features extracted from the segmented regions and the gray level profiles of the radiographs as input for the classifiers.

Table 1 is a guideline for readers' better understanding of the references cited in the text; it also summarizes the main technical specifications and results obtained by some publications mentioned in both parts of this article.

Detection and Classification Based on Feature Extraction

Examining the features of the discontinuities is one of the most widely used techniques for the detection (Mery and Berti, 2003) and classification of weld discontinuities (Aoki and Suga, 1999; Shafeek et al., 2004a; Shafeek et al., 2004b; Silva et al., 2001; Silva et al., 2002a; Silva et al., 2002b; Silva et al., 2003; Silva et al., 2004a; Silva et al., 2004b). In this case, the proper choice of the most relevant features for the identification of each class is of decisive importance in the process of recognition of the discontinuities by the intelligent system. This choice is often made in a manner similar to the interpretation made by an inspector who, most of the time, first recognizes a type of weld discontinuity in the radiograph from visual geometric or intensity features such as location, shape, length, density (gray level) and aspect ratio, among others. Therefore, an important study is required of the morphology of the discontinuity, with respect to the image level, to optimize the system's performance.

Discontinuity Detection

Gayer et al. (1990) proposed a method in two steps:

- A quick search for potential discontinuities in the X-ray image: assuming that the discontinuities will be smaller than the regular structure of the test piece, potential discontinuities are classified as those regions of the image where higher frequencies are significant. The spectrum of the X-ray image is determined with the help of a fast fourier transformation, which is calculated either row by row or column by column in 32×32 windows. When the sum of the higher frequencies of a window is greater than a given threshold value, the entire window is marked as potentially anomalous. Another possibility is suggested by the authors as part of this task: a window is selected as a potentially anomalous region when the sum of the first derivative of the rows and columns in a window is large enough.
- Identification and location of the true discontinuity: because of the time-consuming nature of this step, only those regions that were previously classified as containing potential discontinuities are studied now. Two algorithms were also developed here. The first leads to a matching between the potential discontinuity and typical discontinuities, which are stored in a library as templates; whenever a large resemblance between the potential discontinuity and a template is found, the potential discontinuity is classified as a true discontinuity. The second algorithm estimates an X-ray image of the test piece free of discontinuities by modeling every line of an interpolated spline function without special consideration for the potentially anomalous region. Following this, the original and the discontinuity-free images are compared. True discontinuities are identified when a large difference occurs compared to the original input image.

Discontinuity Classification

One of the most important contributions to this field of research with respect to discrimination between kinds of discontinuities through the use of shape features was made by Aoki and Suga (1999), who attempted to classify the discontinuities according to the criteria described below.

First, a discontinuity can be classified through its geometric shape, whether it is circular or linear. For example, when a discontinuity has a circular shape, it can be classified according to porosity and slag inclusion from the shape outline, the contrast or the position in the weld seam. When a discontinuity has a linear shape and is located on the edge of the seam, it is probably an undercutting, and when it is located in the middle of the seam, the discontinuity can

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Table 1 Main technical aspects of the techniques used by the authors cited in both parts of this paper

Authors	Acquisition	Pre-processing	Segmentation/ Detection	Features (Selection)	Type of Classifiers	Results
Wang and Liao	scanner	median filter; contrast improvement	subtraction of background; histogram thresholding	geometric and intensity	neural networks	≈ 92.0%*
Liao	scanner	gray profiles	extraction from seam and detection	geometric extracted from seam	specific algorithm; neural networks; fuzzy	100.0% (extraction); 93.3% (detection)
Shafeek	CCD camera	histogram extension and equalization; median filter	isolation of seam; local threshold; algorithm of chain code	geometrics	decision tree	visual detection; no percentage provided
Aoki	CCD camera	histogram equalization	subtraction of background	geometric (empirical test)	neural networks	≈ 90.0%
Murakami	vidicon camera	low-pass filter	sequence of high-pass filters	geometric	decision tree	no percentage provided
Cherfa	scanner	noise elimination; contrast extension; median filter	detection of edges; growth of region	geometric	simple limits	no percentange provided
Jacobsen	scanner		high-pass, FFT and morphologic filters	profile measurements	neural networks; learning vector quantization; fuzzy-artmap	≈ 96.67 (networks); ≈ 92.05 (LVQ); ≈ 94.10 (LVQ)
Nafà	not provided	contrast improvement	3x3 neural network edge detection; closure algorithm	window of 3x3 pixels (geometric [invariant moments])	neural networks	96.0%
Liscanner	gray	gray profiles; profiles	gray profiles seam extraction and anomaly identification	fuzzy K-NN (extracted from the profiles)	≈ 86.9%)	(anomalies); ≈ 93.2% (weld)
de Padua	scanner	gray profiles; Savitzky-Golay filter; normalization of anomaly position		gray profiles	neural networks	anomaly identification (88.0%)†
Silva	scanner	median filter and histogram equalization	local threshold	geometric and intensity (linear correlation, neuronal relevance)	neural networks	visual detection; accuracy of classification ≈ 85.0%‡
Mery	film scanner	median, contrast extension	laplacian of gaussian, zero crossing	textural (ROC curves, Fisher's criterion)	limit; polynomial; Mahalanobis nearest neighbor	100.0% of TP and 0.0% of FP

* accuracy estimation: bootstrap and cross validation (5 sets)
† accuracy estimation: random selection
‡ accuracy estimation: random selection (10 sets) and bootstrap (50 sets)

be classified as a crack or lack of penetration. In the study of Aoki and Suga (1999), 10 features are defined to discriminate among the kinds of discontinuities (porosity, slag inclusion, fissure, lack of penetration and undercutting). These features are described below.

- C_1: position of the discontinuity in the weld seam ($C_1 = h/H$), where h is the distance from the discontinuity to the middle of the seam and H is half the width of the seam
- C_2: ratio of the horizontal (F_h) and vertical (F_v) length of the discontinuity ($C_2 = F_h/F_v$)
- C_3: ratio of the length and the area (A) of the discontinuity ($C_3 = M/A$)
- C_4: ratio of the width size (N) and the area (A) of the discontinuity ($C_4 = N/A$)
- C_5: complexity, measured as the ratio of the perimeter (L) squared and the area (A) of the discontinuity ($C_5 = L^2/A$)
- C_6: shape coefficient measured as $C_6 = \pi d^2/4^A$, where d is the greater diameter and A is the area of the discontinuity
- C_7: heywood diameter: the diameter of a circle that has the same area as the discontinuity ($C_7 = [4A/\pi]^{0.5}$)

- C_8: average intensity: average of the gray levels of the discontinuity
- C_9: intensity dispersion: the variance of the gray levels in the discontinuity
- C_{10}: contrast: the intensity difference between the gray levels inside and outside the discontinuity.

To recognize the kind of discontinuity, Aoki and Suga (1999) used neuronal networks. They worked with a supervised two-layer neuronal network with backpropagation type training, with seven neurons in the hidden layer and five neurons in the output layer (five discontinuity classes). They used 35 radiographic models and the data were previously normalized so that they were between 0 and 1. The neuron with the largest value in the output layer determined the discontinuity class.

To verify the effectiveness of each feature in the discrimination between the discontinuity classes studied, Aoki and Suga (1999) evaluated the performance of the network, removing one feature at a time, and concluded that the best performance was that of the situation in which they used all the features. They made a histogram with the performance of the network for each situation (without the presence of a characteristic). Of 27 discontinuities analyzed, 25 were classified correctly, a success rate of 92.6%.

Jacobsen et al. (1998) classified the undercutting and longitudinal crack discontinuities in radiographs of stainless steel welds, using neuronal networks in a training algorithm with backpropagation. Their results indicate a test data success rate of 97.0% for cracks and 90.0% for undercuttings and a training data success rate of 82.5% for cracks and 88.74% for undercuttings. These result, not accounted for by the authors, are peculiar, since normally the best results are obtained with the training data. They also made an evaluation of the relevance of features using neuronal networks, in which they changed the value of a feature and then verified the variation of the network's response to that change.

Kato et al. (1992) used 10 features to classify discontinuities: porosity, lack of melting, lack of penetration, crack and tungsten inclusion. They suggest that the discontinuities can be classified visually into linear and circular. Based on that, they defined characteristics: length, width, symmetry and roundness, among others. Furthermore, they also defined features: angle (between the main axis of the discontinuity and the middle line of the seam), position (with respect to the middle of the seam) and gray-level density of the discontinuity, among others. They also commented on the difficulty of finding features to identify the typical welding discontinuities based only on information from the radiograph inspectors, because even those with more experience often do not justify the use of some features to distinguish certain classes of discontinuity. For that reason, they point out the need to use other information such as the material welded, welding technique used, welding conditions and radiograph testing technique used.

Yue et al. (1998) refers to some rules with respect to the relation between the geometric features and classes of welding discontinuities according to international standards. They are:

- if the length/width ratio is less than 3, then the discontinuity is linear; otherwise, it is spherical
- if the discontinuity has a smooth outline, then it is porosity; otherwise, it is spherical slag inclusion
- if the direction of the discontinuity orientation is horizontal, then the discontinuity is horizontal; otherwise, it is a crack.

Lashkia (2001) comments that the discontinuities can basically be classified into three classes according to their visual features: rounded discontinuities (porosity, slag inclusion, lack of penetration), longitudinal discontinuities (lack of melting, lack of penetration, fissure) and transverse discontinuities (fissure).

Wen et al. (1993) described the features of welding discontinuities as follows:

- porosity: circular dark points of the film, smooth outline, gray levels that are low (dark) at the center and high (light) near the edge
- inclusion: shape of a stretched or circular "bar," nonuniform gray levels and edges not smooth like in the porosities; random location along the seam
- lack of fusion: location between the middle and the edge of the seam, stretched and narrow shape with irregular outline
- lack of penetration: located in the middle of the seam, with a stretched shape and smooth and regular outline
- crack: irregular location, size and orientation in the weld (very narrow and irregular shape).

Silva et al. (2001; 2002a; 2002b; 2003; 2004a) used a set of geometric features such as roundness, aspect ratio and location of the discontinuities, among others, to classify the kinds of discontinuities: lack of penetration, undercutting, pore, crack, slag inclusion and lack of fusion in linear and nonlinear classifiers, implemented by artificial neuronal networks. The success rate with the linear classifiers was 85%, but using a larger set of radiographic models and the nonlinear classifiers, the accuracy was significantly higher on test samples (Silva et al., 2004a). Silva et al. (2002b; 2004a) carried out a study of the relevance of welding discontinuity features in radiographs by implementing the line correlation and neuronal relevance criterion, showing that what is important is the quality and not the number of features used in the model vector, allowing characteristics that are irrelevant to the classification system to be eliminated. Another important aspect of this work is the use of main nonlinear discrimination components as a resource for the two-dimensional visualization of the class representation space and as input data for the classifiers (Silva et al., 2004a).

Mery and Berti (2003) proposed an approach based on two texture features: features based on the co-occurrence matrix, which gives a measurement of how often one gray value will appear in a specified spatial relationship to another gray value on the image; and features based on 2D Gabor functions, that is, gaussian-shaped bandpass filters, with dyadic treatment of the radial spatial frequency range and multiple orientations, which represent an appropriate choice for tasks requiring simultaneous measurement in both space and frequency domains. In the experiments, the detection rate was 91%, though the false positive rate was 8%.

For discontinuity recognition, Nafâ and Drai (2000) used the regular moments of the digital images. Using a nonlinear combination of the normalized central moments, they derived the seven moments of Hu, which had the property of being invariant to translation, scale and rotation of the image. Then, those seven moments were used as input characteristics in a neuronal network of the backpropagation type, with two layers and neurons with hyperbolic tangent function. The number of neurons in the hidden layer was determined empirically.

Wang and Liao (2002) published a paper in which they describe the following features for classifying the discontinuities:

- distance from the middle of the seam: distance from the middle of the discontinuity to the middle line of the seam
- mean ray, deviation patterns and circularity: features for measuring the degree of circularity of a discontinuity (see details in Wang and Liao [2002])
- roundness: another feature for measuring the circumferential degree of a discontinuity
- major axis: orientation of the extension of the discontinuity in the weld, calculated as the angle between the length of the discontinuity and a horizontal line
- width and length: width and length of the smallest box surrounding the discontinuity
- elongation: a shape feature very well known as aspect ratio, that is, the ratio of the width and the length of the discontinuity
- heywood diameter: diameter of a circle with an area equivalent to that of the discontinuity
- mean intensity and deviation of intensity patterns: information on the brightness of the discontinuity in the radiograph.

Wang and Liao (2002) used this set of features to form the input and output data of two nonlinear classifiers: one using a two-layer neuronal network and the other implemented by the fuzzy K-NN algorithm. In these classifiers, Wang and Liao (2002) classified six classes of discontinuities: crack, gas hole, porosity, hydrogen inclusion, lack of penetration and lack of fusion. In their paper, they stressed that, because there is a reduced set of observations for these classes, they used techniques like cross validation and bootstrap to verify the performance of their classifiers. The best results obtained by the neuronal networks, and similarly by the fuzzy classifiers, reached an average of 92.3% success for the test data, a rate that can be considered as very good.

In the field of classification of models, regardless of the classifiers used, it is important to know which is the actual accuracy of the classifiers, that is, which is the level of success estimated for the data samples not used in the training of the classifiers. There are various techniques for estimating the actual accuracy of a classifier normally involving random test and training samples, such as cross validation and bootstrap techniques. In weld radiographs, the pioneering work of Wang and Liao (2002) for estimating the accuracy of the classification of welding discontinuities using the bootstrap technique with five test sets stands out. Recently, Silva et al. (2004b) used the bootstrap technique with 50 random sets to estimate the accuracy of the classification of six classes of discontinuities, in that way reaching about 85% of the estimated accuracy.

Weld Extraction, Detection and Classification Based on Gray Level

Another line of research for the development of an automated system of radiographic analysis of continuous welds is the one that aims at detecting the discontinuities via the gray level profile transverse to the weld seam. Figure 1 shows two typical examples of profiles transverse to the weld seam from the paper by Pádua et al. (2004), one in the absence of a discontinuity (Figure 1a) and the other one with a discontinuity (Figure 1b).

Weld Extraction

Li and Liao (1996) primarily used a technique for extracting the weld seam from the radiographic image for later identification of the discontinuities. They analyzed three features of the weld seams: width of the object, mean square error between the discontinuity's profile and a gaussian curve, and intensity of the object's peak. According to the authors, an intensity profile of the weld seam behaves more like a gaussian curve than other objects present in the image.

To verify the discriminating capacity of these classes of "weld" and "no weld," Li and Liao (1996) used the criteria of distance between the mean values of the features of each class, as well as the overlapping between the classes. For the distance criterion, they concluded that the object's width feature was the best, and for the overlapping criterion the mean square error feature showed the best performance. Using these two features, they used a total of 44 data in the K-NN fuzzy logic algorithm to classify the classes, achieving a 93.2% performance for the situation in which the data were normalized.

Liao and Tang (1997) evaluated the possibility of extracting the weld seams using neuronal networks. They consider that the extraction of welds from the X-ray images is a segmentation problem, finding that it is impossible to apply a simple cut at the gray level in the histogram of the radiograph to segment it. Therefore, they used multiple cuts as follows: if the gray level is between 25 and 50, then the output is 0 (black); otherwise it is 255 (white).

However, Liao and Tang (1997) did not get good results using only this technique. They also worked with neuronal networks to extract the seam from the radiographic image. For that purpose, they first defined the features capable of discriminating a weld from the rest of the image. These features were extracted from the transverse gray profile of the seam's image. They were peak position, peak width, mean square error between the profile of the weld and a gaussian curve, and peak intensity. First, the system operated with an algorithm for detecting peaks and objects in the image, based on the detection of changes in the tangent to the profile's line at each point. For every object detected, the intensity and position of the peak were determined. Then an algorithm was applied to detect the values associated with the peaks/objects found. After finding the values, the width of each object was measured and the mean square error was calculated.

Following the stages described above, a neuronal network of the backpropagation type with two layers was used, using the moment and training in epoch, to classify the inputs into two classes: weld and no weld. Liao and Tang (1997) used the technique of Fletcher-Reeves for training the network, comparing its performance with the backpropagation technique. With the classification of the neuronal network, the result was then a binary image with the weld in white and the background in black. To eliminate classification errors, a postprocessing system was applied, optimizing the results. They used a set of validation data to determine the network's optimum parameters. The comparison between the two training sets

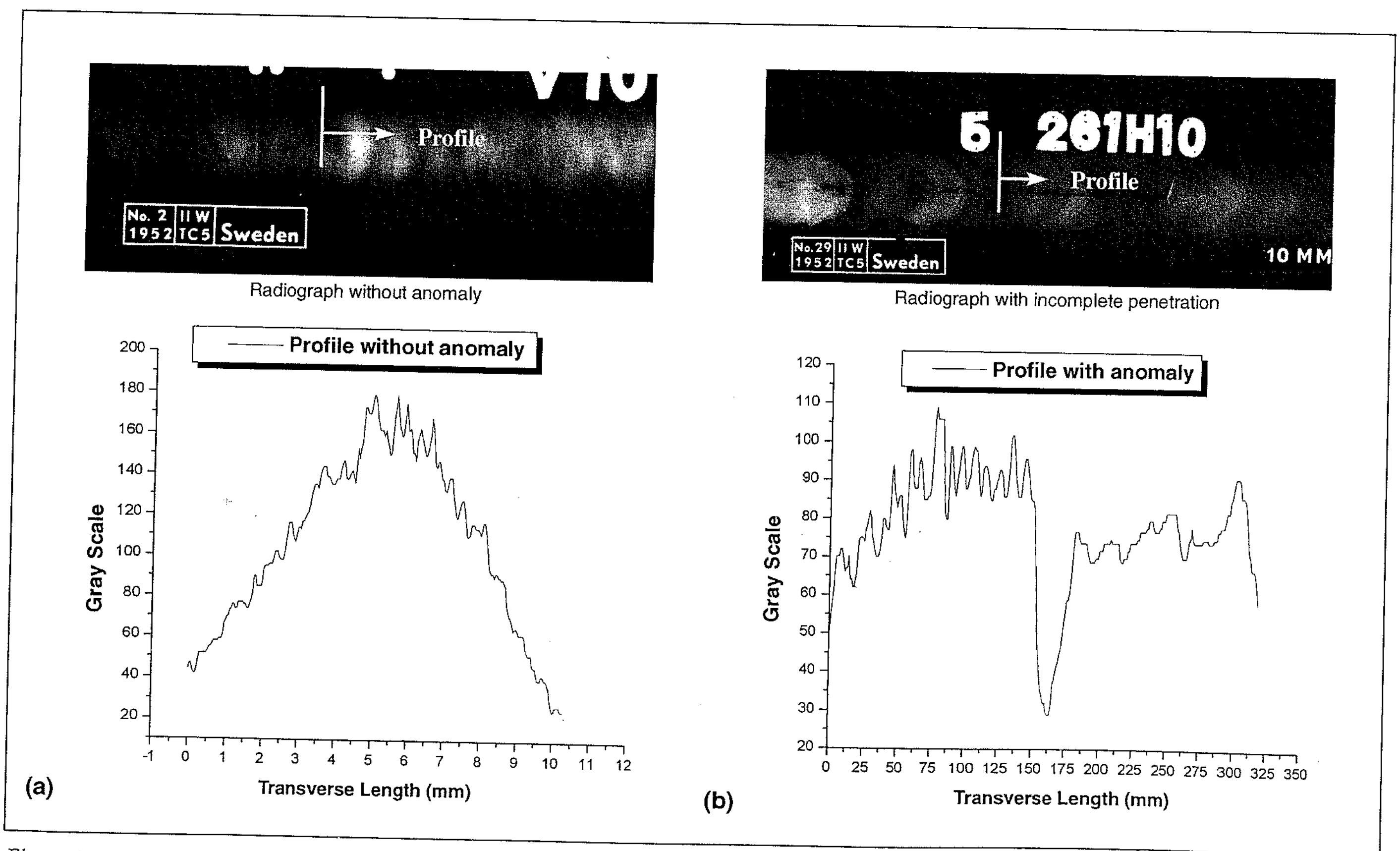

Figure 1 — Samples of a grayscale profile: (a) without discontinuity; (b) with incomplete penetration (Padua et al., 2004).

showed that the Fletcher-Reeves gave better results. They also carried out a series of tests with the networks, trying to achieve the best possible configuration, concluding that the network with seven neurons in the intermediate layer had better performance, allowing 100% accuracy in the classification of welds.

Liao and Ni (1996) extracted the weld seam from the digital radiographic image using Khoros software, but in this case they did not use the neuronal networks for the classification of the seams. They described the 15 stages that make up the seam extraction algorithm. The results showed the full efficiency of the methodology (100% success) for the extraction of weld seams that have linear edges, but they stressed the need for further development of this technique for the case of seams with rounded edges.

Another interesting work is from Felisberto et al. (2006), whose research was to develop and implement a system for weld seam extraction from a digital radiography, but not using gray level profile. The proposed methodology uses a genetic algorithm to manage the search for suitable feature values (position, width, length and angle) that best defines a window in the radiographic image, matching with the model image of a weld bead simple (Felisberto et al., 2006).

Discontinuity Detection and Classification

In another publication, Liao and Li (1998) described the second part of the work, which consisted in the development of an automatic system of radiographic testing that deals with the detection of the seam's discontinuities. The methodology used was based on the observation that an intensity profile of the gray levels transverse to the weld seam has the shape of a perfect bell. If a weld discontinuity appears in the weld, the result is an anomaly in the profile's format. This anomaly was classified into three categories: peak, valley and concave slope.

The detection technique of Liao and Li (1998) comprises four main stages: preprocessing module, curve adjusting module, anomalous profile detection module and postprocessing module. The preprocessing module was used to remove the background and normalize all the images at the same gray level. The curve adjusting module was used to smooth the profiles by applying filters on the local variations. The anomalous profile detection module detects the existence of anomalies in the profiles. Then the results obtained from the profiles were collected to generate a two-dimensional map of the discontinuity. The postprocessing module removed isolated anomalies that had been identified in a previous stage and updated the maps of the discontinuities.

In the discontinuity detection module, which Liao and Li call anomalous peak detection (1998), some concepts are defined that were used in the system to find the peaks in the profiles that could be interpreted as welding discontinuities, such as (Figure 2):

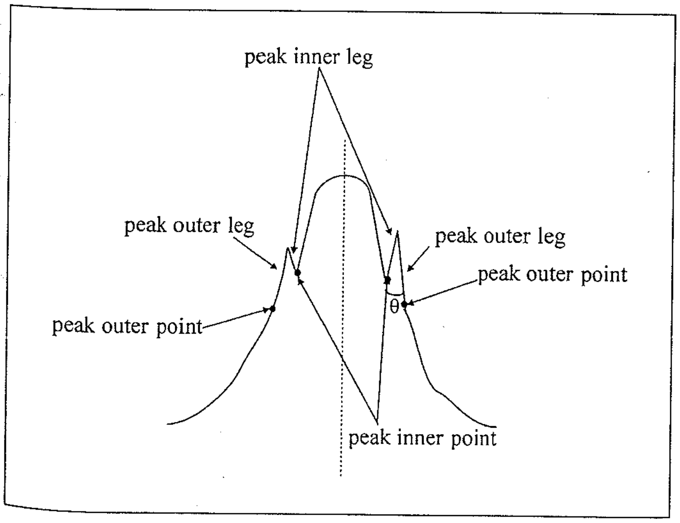

Figure 2 — Illustration of the principle of discontinuity detection in Liao's profiles (adapted from Liao and Li [1998]).

- inner and outer *leg* of the peak: the inner leg is defined as the one closest to the middle line, and the outer leg is the one farthest from it
- peak angle θ: angle between the two legs, outer and inner
- pointy peak: if the peak angle is smaller than a given threshold value, it is considered pointy; a peak is doubly pointy if its angle is smaller than half the threshold value
- inner and outer points of the peak: the point at which the outer/inner leg of the peak starts describing a bell curve is defined as the outer/inner point.

Using the above definitions, an anomalous peak, which probably indicates a discontiniuity, normally has the following characteristics:

- if the peak is doubly pointy, it is considered anomalous
- a pointy peak may or may not be anomalous; further information is required to confirm it
- the outer leg of an anomalous peak is usually less than twice the size of the smaller one
- the tangent to the outer leg of a peak is high
- if a peak is pointy and its corresponding gray level is the largest on the profile line, it is usually an anomalous peak.

Based on the above features, an algorithm was developed for the detection of anomalous peaks as described in that paper. After some experiments with 24 images that contained 75 discontinuities, Liao and Li (1998) obtained 93.3% success with his system, considered an excellent result.

On the other hand, Kazantsev et al. (2002) describe a different way of research to detect weld discontinuities in radiographic images by using statistical hypothesis testing with several nonparametric tests.

Also using gray level intensity profiles transverse to the seam is the work of Jacobsen et al. (1998), which is very interesting. They used filters in the frequency domain, in one dimension, to detect fissures and undercuts in the radiographs. To enhance the visibility and the indications of longitudinal fissures, they used a high-pass filter (Bessel operator) developed at the Federal Institute for Materials Research and Testing (BAM) in Berlin. To filter frequencies equal to or higher than the frequency related to the presence of the fissure discontinuity, it was possible to separate the two classes of discontinuities.

Pádua et al. (2004) worked with gray level profiles for the detection and classification of the weld seam in radiographic models, in a procedure with an objective similar to that of Liao and Ni's technique (1996), but using classifiers implemented by artificial neuronal networks. For preprocessing the data, they initially smoothed the noise in the gray level signal using the Savitzky-Golay filter. The choice of filter was based on the fact that it produces a smaller amplitude decreases of a valley/peak discontinuity than one caused by a moving average type filter. Later, to normalize the position of the discontinuities with respect to the center of the adjusted gaussian curve based on the filtered profile, all the profiles that had discontinuities to the left of the middle of the gaussian were inverted in the ordering of the points. This procedure sought to facilitate the optimization of the performance indices of the classifiers due to the large variation in the position of most of the classes of discontinuities within the seam. Padua et al. (2004) got 80% accuracy in the discontinuity detection test when only the smoothed profiles were used in the training and in the test of the nonlinear classifiers, and a test accuracy of 88% when the profiles were normalized according to the distribution of the discontinuities, showing that the preprocessing of the profiles is extremely important in this case.

The work of Nafâ and Drai (2000) differs from that discussed above in that it does not use gray level profiles. To detect the edges of the discontinuity, they used windows of 3×3 pixels placed along the weld seam as backpropagation of the error. In this case, each element of this window was a gray level corresponding to the image's pixel. The output layer had only one neuron for classifying in the output the detection or nondetection of the edge of a discontinuity, finally forming a segmented (binary) image. As training pairs of the network, use was made of 28 outline models. The authors stressed that the results were satisfactory when, before using the neuronal network to segment the image, an optimizing treatment of the contrast of the radiographs was made. They tested their radiography system with and without the presence of noise, concluding that the network smoothed the noise existing in the images.

FINAL CONSIDERATIONS

Analyzing the main publications in this research area, it can be firmly stated that there are no well established rules which, when followed, will lead to an automatic system of radiographic testing. Several techniques are used by the authors, some of them very similar, as can be seen in the references cited.

With respect to the classification of discontinuities, in most of the papers pattern recognition is carried out using neuronal networks. Many of the papers (Aoki and Suga, 1999; Jacobsen et al., 1998; Jagannathan, 1997; Jagannathan et al., 2000; Just et al., 1998; Liao and Tang, 1997; Wang and Liao, 2002; Yue et al., 1998; Zhang and Basart, 1995) make some considerations on the shape of the discontinuities to choose the most relevant features for discriminating between the common welding discontinuities. Wang and Liao (2002) point out the still insufficient research in this development stage of the field, reminding us that there still is no commercial automatic analysis system for continuous radiographs. There is no doubt, however, of the increasing number of researchers involved in the development of such system, motivated by the technological and economic advantages that it would provide to those who sell and buy radiographic testing services and equipment.

In conclusion, on the basis of all the papers described, further development of the segmentation (detection) stage is needed, considering the difficulties that still exist, which will certainly guide future research. The authors believe that it may be worthwhile to work with gray level profiles as an input set, since in this way the segmentation step of the weld seam is not necessary.

ACKNOWLEDGMENTS

This work was supported in part by FONDECYT – Chile (International Cooperation), under grant number 7060170. The authors wish to thank Rachel Monnier for translation support. This work has been partially supported by a grant from the School of Engineering at Pontificia Universidad Católica de Chile.

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