State-of-the-Art of Weld Seam Radiographic Testing: Part II – Pattern Recogtion

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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 defects 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 defects segmented in the images. Because of the complexity of the problem of detecting weld defects, a large number of techniques have been investigated in these areas. This paper represents a state-of-the-art report on weld inspection 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 defects in continuous welds. This paper deals with the second part.

KEYWORDS: Weld defects, nondestructive testing, radiography, automatic weld inspection, image analysis, pattern recognition.

1. INTRODUCTION

Part I of this article described almost all the references dealing with image processing of weld radiographs. In this second part, we will discuss the main references on the classification of weld defects in digitized radiographs in the same way as in the first part, i.e., in so far as possible trying to make a comparison between the techniques used and the results obtained by the authors. Finally, a structured chart is presented with a summary of the content of both articles.

2. PATTERN RECOGNITION IN THE DETECTION AND CLASSIFICATION OF WELD DEFECTS

The second, but not less important, part of a system for the identification and classification of welding defects using radiographs includes a number of pattern recognition techniques such as statistical classifiers, neuronal networks, and fuzzy logic [0,1]. The applications, which will be described below, use as input for the classifiers both the features extracted from the segmented regions and the grey level profiles of the radiographs.

Table 1 is a kind of guideline for readers' better understanding of the references cited in the text and also summarizes the main technical specifications and results obtained by some publications mentioned in the two articles (Part I and II).

TABLE 1: *Main technical aspects of the techniques used by the authors cited in our two papers for readers guideline (parts I and II).*

Authors	Acquisition	Pre-processing	Segmentation/ Detection	Features	Features Selection	Type of Classifiers	Accuracy Estimation	Results
G. Wang and T. Warren Liao [31]	Scanner	Median filter; Contrast improvement	Subtraction of background; Histogram thresholding	Geometric and intensity	-	Neural Networks	Bootstrap and Cross Validation (5 sets)	~92.0%
T. Warren Liao [23,24]	Scanner	Grey profiles	Extraction from seam and detection	Geometric extracted from seam	-	Specific algorithm; Neural Networks; Fuzzy	-	100.0% (Extraction) 93.3% (Detection)
H. I. Shafeek[10,11]	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
K. Aoki[32,33]	CCD camera	Histogram Equalization	Subtraction of background	Geometric	Empirical test	Neural Networks	-	~90.0%
K. Murakami[34]	Vidicon camera	Low-pass filter	Sequence of high-pass filters	Geometric	-	Decision tree	-	No percentage provided
Y. Cherfa[35]	Scanner	Noise elimination; Contrast extension; Median filter	Detection of edges; growth of region	Geometric	-	Simple limits	-	No percentage provided
C. Jacobsen[13]	Scanner	-	High-pass filters; FFT filter; morphologic filters	Profile measurements	-	Neural Networks Learning Vector Quantization (LVQ) Fuzzy-Artmap	-	~96.67 (Networks) ~92.05 (LVQ) ~94.10 (LVQ)
N. Nafaâ[18]	Not provided	Contrast improvement	Detection of edges with neural networks with a 3x3 window; Closure algorithm	Window of 3x3 pixels	Geometric (invariant moments)	Neural Networks	-	96.0%
D. Li[21]	Scanner	Grey profiles	Grey profiles	Grey profiles	Extracted from		-	~86.9%

			Extration of seam and identification of defect		the profiles	Fuzzy K-NN		(Defects) ~93.2% (Weld)
Germano. X. de Padua [20]	Scanner	Grey profiles; Savitzky-Golay filter; Normalization of position of defect	-	Grey profiles	-	Neural Networks	Random selection	Identification of defect (88.0%)
Romeu R. Silva[36]	Scanner	Median filter and Histogram Equalization	Local Threshold	Geometric and Intensity	Linear correlation and Neuronal Relevance Criterion	Neural Networks	Random selection (10 sets) and Bootstrap (50 sets)	Visual detection; accuracy of classification ~85.0%
Domingo Mery[37,38]	Film scanner	Median, Contrast extension	Laplacian of Gaussian, Zero Crossing	Textural	ROC (Receiver Operating Characteristic) curves, Fisher's Criterion	Limit; Polynomial; Mahalanobis Nearest neighbor	-	100.0% of TP and 0.0% of FP

2.1 Detection and Classification based on feature extraction

Using the features of the defects is one of the most widely used techniques for the detection [2] and classification of weld defects [3-11]. 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 defects 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 defect in the radiograph from visual geometric or intensity features such as location, shape, length, density (grey level), and aspect ratio, among others. Therefore, an important study is required of the morphology of the defect, with respect to the image level, to optimize the system's performance.

2.1.1. Defect Detection

Gayer et al., [12] proposed a method in two steps: 1) A quick search for potential defects in the X-ray image: Assuming that the defects will be smaller than the regular structure of the test-piece, potential defects 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 a 32 x 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 defective. Another possibility is suggested by the authors as part of this task: A window is selected as a potentially defective region when the sum of the first derivative of the rows and columns in a window is large enough. 2) Identification and location of the true defect: Because of the time-consuming nature of this step, only those regions which were previously classified as containing potential defects are studied now. Two algorithms were also developed here. The first leads to a matching between the potential defect and typical defects, which are stored in a library as templates; whenever a large resemblance between the potential defect and a template is found, the potential defect is classified as a true defect. The second algorithm estimates a defect-free X-ray image of the test piece by modeling every line of an interpolated spline function without special consideration for the potentially defective region. Following this, the original and the defect-free images are compared. True defects are identified when a large difference occurs compared to the original input image.

2.1.2. Defect Classification

One of the most important contributions to this field of research with respect to discrimination between kinds of defects through the use of shape features was made by Aoki & Suga [3], who attempted to classify the defects according to the criteria described below:
First, a defect can be classified through its geometric shape, whether it is circular or linear. For example, when a defect 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 defect 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 defect can be classified as a crack or lack of penetration. In the study of Aoki & Suga [3], ten features are defined to discriminate among the kinds of defects, which are porosity, slag inclusion, fissure, lack of penetration, and underccutting. These features are described below.

- C_1: Position. Location of the defect in the weld seam ($C_1 = h/H$), where h is the distance from the defect 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 defect ($C_2 = F_h/F_v$).

• C_3: Ratio of the length and the area (A) of the defect (C_3 = M/A).
• C_4: Ratio of the width size (N) and the area (A) of the defect (C_4 = N/A).
• C_5: Complexity, measured as the ratio of the perimeter (L) squared and the area (A) of the defect ($C_5 = L^2/A$).
• 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 defect.
• C_7: Heywood Diameter. The diameter of a circle that has the same area as the defect ($C_7 = \sqrt{4A/\pi}$).
• C_8: Average intensity. Average of the grey levels of the defect.
• C_9: Intensity dispersion. The variance of the grey levels in the defect.
• C_{10}: Contrast. The intensity difference between the grey levels inside and outside the defect.

To recognize the kind of defect, Aoki & Suga [3] used neuronal networks. They worked with a supervised 2-layer neuronal network with backpropagation type training, with seven neurons in the hidden layer and five neurons in the output layer (five defect 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 defect class.

To verify the effectiveness of each feature in the discrimination between the defect classes studied, they 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 feature. Aoki & Suga [3] made a histogram with the performance of the network for each situation (without the presence of a characteristic). Of 27 defects that were analyzed, 25 were classified correctly, equivalent to 92.6% of success.

Jacobsen et al. [13], to classify the undercutting and longitudinal crack defects in radiographs of stainless steel welds, used neuronal networks in a training algorithm with backpropagation. Their results indicate a success rate of 97.0% for crack and 90.0% for undercuttings with the test data, and 82.5% for crack and 88.74% for undercuttings with the training data. This result, not accounted for by the authors, is 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. [14] used ten features to classify the defects: porosity, lack of melting, lack of penetration, crack, and tungsten inclusion. They suggest that the defects can be classified visually into linear and circular. Based on that, they defined the characteristics: length, width, symmetry, and roundness, among others. Furthermore, they also defined the features: angle (between the main axis of the defect and the middle line of the seam), position (with respect to the middle of the seam), and grey level density of the defect, among others. They also commented on the difficulty for finding features to identify the typical welding defects based only on information by the radiograph inspectors, because even those with more experience often do not justify the use of some features to distinguish a certain class of defect. For that reason they point out the need to use other information such as material welded, welding technique used, welding conditions, and radiograph inspection technique used.

Yue [15] refers to some rules with respect to the relation between the geometric features and classes of welding defects according to international standards. They are:

• If the length/width ratio is >3, then the defect is linear; otherwise it is spherical.
• If the defect has a smooth outline, then it is porosity; otherwise it is spherical slag inclusion.
• If the direction of orientation of the defect is horizontal, then the defect is horizontal; otherwise it is a crack.

Lashkia [16] comments that the defects can basically be classified into three classes according to their visual features: rounded defects (porosity, slag inclusion, lack of penetration), longitudinal defects (lack of melting, lack of penetration, fissure) and transverse defects (fissure).

Wen et al. [17] described the features of welding defects as follows:
• Porosity: circular dark points of the film, smooth outline, grey levels that are low (dark) at the center and high (light) near the edge.
• Inclusion: shape of a stretched or circular “bar”, nonuniform grey 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 [4,5-8] used a set of geometric features such as roundness, aspect ratio, and location of the defects, among others, to classify the kinds of defects: 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 85% higher on test samples [8]. Silva et al. [6,8] carried out a study of the relevance of welding defect 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 [8].

Mery & Berti [2] proposed an approach based on two texture features: 1) features based on the co-occurrence matrix, which gives a measurement of how often one grey value will appear in a specified spatial relationship to another grey value on the image; and 2) features based on 2D Gabor functions, i.e., 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%, however the false positive rate was 8%.

For defect recognition, Naffaâ & Redouane [18] 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.

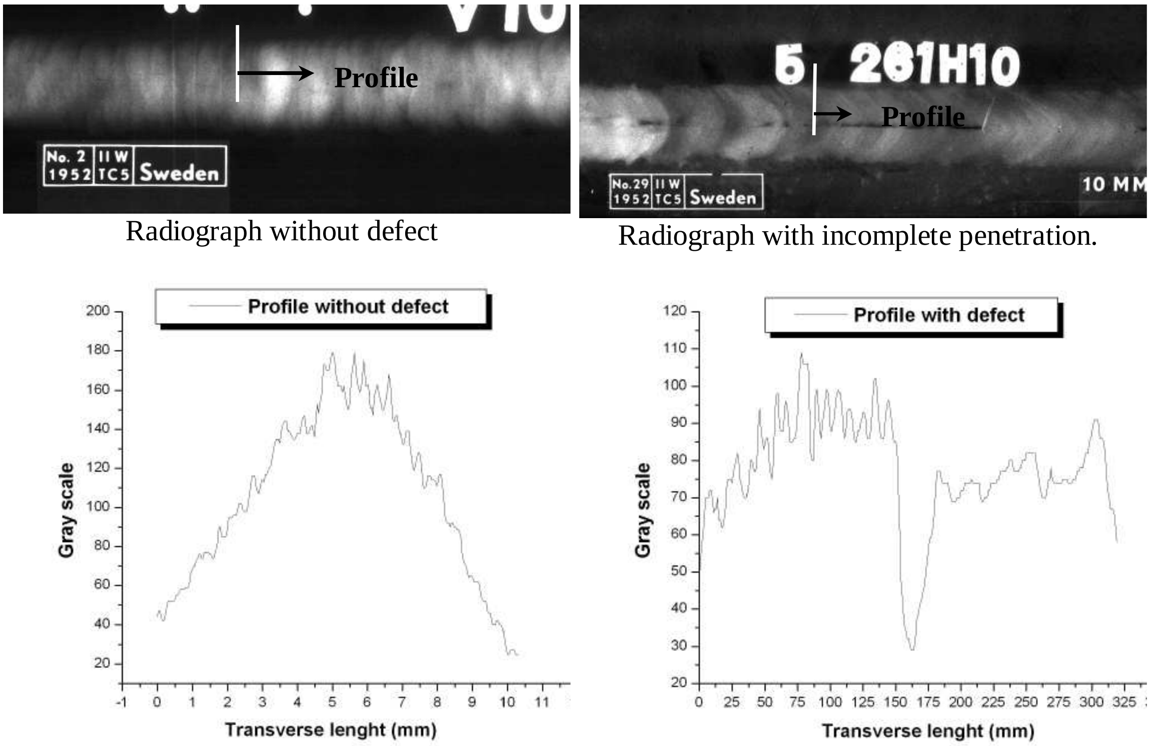
Wang & Liao [19] published a paper in which they describe the following feature for classifying the defects:
• Distance from the middle of the seam: distance from the middle of the defect to the middle line of the seam.
• Mean ray, deviation patterns and circularity: features for measuring the degree of circularity of a defect (see details in [19]).
• Roundness: another feature for measuring the circumferential degree of a defect.
• Major axis: orientation of the extension of the defect in the weld, calculated as the angle between the length of the defect and a horizontal line.
• Width and Length: width and length of the smallest box surrounding the defect.
• Elongation: a shape feature very well known as aspect ratio, i.e., the ratio of the width and the length of the defect.
• Heywood Diameter: diameter of a circle with an area equivalent to that of the defect.
• Mean intensity and deviation of intensity patterns: information on the brightness of the defect in the radiograph.

Wang & Liao [19] 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 & Liao [19] classified 6 classes of defects: crack, pore, porosity, hydrogen inclusion, lack of penetration. In their paper they stressed that, because there is a reduced set of observations for these classes, they used methods 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, what is important is to know which is the actual accuracy of the classifiers, i.e., 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 & Liao [19] for estimating the accuracy of the classification of welding defects using the Boostrap technique with five test sets stands out. Recently, Silva et al. [9] used the Bootstrap technique with 50 random sets to estimate the accuracy of the classification of 6 classes of defects, in that way reaching about 85% of the estimated accuracy.

2.2 Weld Extraction, Detection and Classification based on grey 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 defects via the grey 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 [20], one in the absence of the defect, Figure 1(a), and the other one with the defect, Figure 1(b).



(a) (b)

FIGURE 1: *Examples of a greyscale profile without defect (a) and with incomplete penetration (b) [20].*

2.2.1. Weld Extraction

Li [21] used, primarily, a technique for extracting the weld seam from the radiographic image for later identification of the defects. He analyzed three features of the weld seams: width of the object, mean square error between the defect's profile and a Gaussian curve, and intensity of the object's peak. According to Li [21], 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 [21] 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 he 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, he used a total of 44 data in the K-NN fuzzy logic algorithm to classify the classes of weld and no weld, achieving a 93.2% performance for the situation in which the data were normalized.

Liao & Tang [22] 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 grey level in the histogram of the radiograph to segment it. Therefore, he used multiple cuts as follows:

- If the grey level is between 25 and 50, then the output is 0 (black); otherwise it is 255 (white).

However, Liao & Tang [22] 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 grey 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 & Tang [22] used the technique of Fletcher-Reeves for training the network, comparing its performance with the backpropagation method. 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 post-processing 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 trainings showed that the Fletcher-Reeves gave better results. Liao & Tang [22] 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 [23] extracted the weld seam from the digital radiographic image using the *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 method for the case of seams with rounded edges.

Another interesting work is from Felisberto [25], whose research was to develop and implement a system to 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 features 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 [25].

2.2.2. Defect Detection and Classification

In another publication [24], Liao and Li described the second part of the work, which consisted in the development of an automatic system of radiographic inspection which deals with the detection of the seam's defects. The methodology used was based on the observation that an intensity profile of the grey levels transverse to the weld seam has the shape of a perfect "bell". If a weld defect 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 method of Liao [24] comprises four main stages: pre-processing module, curve adjusting module, anomalous profile detection module, and post-processing module. The pre-processing module was used to remove the background and normalize all the images at the same grey 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 defect. The post-processing module removed isolated anomalies that had been identified in a previous stage and updated the maps of the defects.

In the defect detection module, which Liao calls anomalous peak detection [24], some concepts are defined that were used in the system to find the peaks in the profiles that could be interpreted as welding defects, such as (see Figure 2):

• 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.

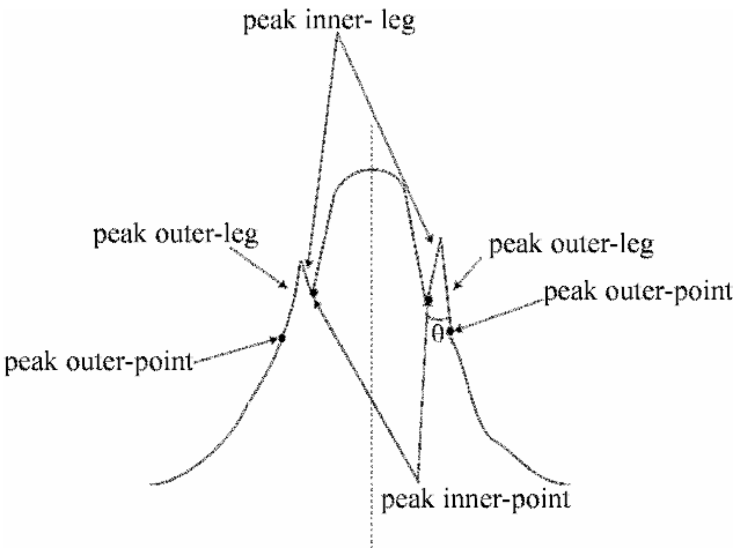


FIGURE 2: *Illustration of the principle of defect detection in Liao's profiles (figure adapted from Liao [24]).*

Using the above definitions, an anomalous peak, which probably indicates a defect, 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 grey 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 defects, Liao obtained 93.3% success with his system, which he considered an excellent result [24].

On the other hand, Kazantsev [26] describes a different way of research to detect weld defects in radiographic images by using statistical hypothesis testing with several nonparametric tests.

Also using grey level intensity profiles transverse to the seam there is the work of Jacobsen [13], which can be considered very interesting. He used filters in the frequency domain, in one dimension, to detect fissures and undercuts in the radiographs with which he worked. To enhance the visibiliy and the indications of longitudinal fissures, Jacobsen [13] 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 presencence of the fissure defect, it was possible to separate the two classes of defects.

Padua [20] worked with grey 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's technique [23], but using classifiers implemented by artificial neuronal networks. For pre-processing the data, he initially smoothed the noise in the grey level signal using the filter of Savitzky-Golay. The choice of filter was based on the fact that it produces a smaller amplitude decrease of a valley/peak defect than one caused by a moving-average type filter. Later, to normalize the position of the defects with respect to the center of the adjusted Gaussian curve based on the filtered profile, all the profiles that had defects 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 defects within the seam. Padua [20] got 80% accuracy in the defect detection test when he used only the smoothed profiles in the training and in the test of the nonlinear classifiers, and a test accuracy of 88% when the profiles were even normalized according to the distribution of the defects, showing that the pre-processing of the profiles is extremely important in this case.

The work of Naffaâ [18] differs from that discussed above in that it does not use grey level profiles. To detect the edges of the defect he used windows of 3x3 pixels placed along the weld seam as backpropagation of the error. In this case, each element of this window was a grey 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 defect, finally forming a segmented (binary) image. As training pairs of the network, use was made of 28 outline models. Naffâ [18] 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. He tested his radiography system with and without the presence of noise, concluding that the network smoothed the noise existing in the images.

3. 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 inspection. 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 defects, in most of the papers pattern recognition is carried out using neuronal networks. Many of the papers (Aoki [3]; Wang [19]; Liao [22]; Jacobsen [13]; Yue [15]; Just [27]; Jagannatan [28,29]; Zhang [30]) make some considerations on the shape of the defects to choose the most relevant features for discriminating the common welding defects. Wang [19] points out the still insufficient research in this development stage of the field, reminding us that there still is no commercial automatic system of analysis of 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 inspection 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. On the other hand, we believe that it may be a good suggestion some new developments by working with gray level profiles as input set, since in this way the segmentation step of the weld seam is not necessary.

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