CONTRIBUTION TO THE DEVELOPMENT OF A RADIOGRAPHIC INSPECTION AUTOMATED SYSTEM

Romeu Ricardo da Silva[1], Marcio H. S. Siqueira[1], Luiz P. Calôba[2], Ivan C. da Silva[1], Antonio A. de Carvalho[1] and João Marcos A. Rebello[1].

[1]Department of Metallurgical and Materials Engineering and
[2]Department of Electrical Engineering, Federal University of Rio de Janeiro (UFRJ),
P.O Box 68504 CEP 21945-970 Rio de Janeiro RJ Brazil
E-mail: romeu@metalmat.ufrj.br

Abstract

With the advances in information technology and artificial intelligence techniques, like neural networks and fuzzy logic, the opportunity arose to develop a radiographic inspection method capable of detecting and classifying welding defects automatically, minimizing the subjective evaluation errors inherent to the conventional method. The key objectives in this work are to evaluate how relevant the characteristic parameters from welding defects are, by means of the linear correlation technique, as well as to utilize the relevant parameters in a linear classifier of patterns developed with the use of neural networks. The obtained results attest the efficiency of the technique used, representing an important step toward the development of a radiographic inspection automated system.

Introduction

Radiographic inspection has a life history of over half a century amidst nondestructive testing. For this reason, it is prominent in several industrial specializations, most importantly with regard to the inspection of welded joints.

In radiographic welded joint inspections, several parameters are controlled during the examination in order to produce an image that will allow detection of welding defects that occur in the welding bead. After examination, even under strict control, the radiographic films show deficiencies that prevent an adequate inspection. Problems such as the presence of noise and insufficient contrast are frequently found on conventional radiographs.

The correct interpretation of the radiograph at the end of the examination will depend essentially on the image quality and on the interpreter's experience in his evaluation. First, in order to identify the most common welding defects on radiographs after their detection, morphological parameters are observed like geometric shape, lenght, width, gray level (density), as well as its location on the welding bead. Since this criterion makes evaluation subjective because it depends on each inspector's experience, refinement of this process is necessary in order to reduce the interpretation error.

Concurrently with the advances in information technology and with the development of artificial intelligence related techniques, especially neural networks and Fuzzy logic, research geared toward the development of radiographic inspection automated systems have increased considerably in recent years[1-8]. The majority of these automatic systems frequently involve a

film digitizing step, an image preprocessing step (application of digital filters and contrast improvement), and finally a defect detection step.
In this paper some characteristic parameters are evaluated according to their relevance in discriminating the following defect classes: undercutting, lack of penetration, porosity and slag inclusion, by using a linear correlation matrix. The most relevant parameters are used as input data on a hierarchic linear pattern classifier, implemented by neural networks.

Experimental Methodology

Radiographic Film Digitizing

Radiographs were digitized on a UMAX flatbed scanner model Mirage II with a resolution of 400 dpi (dots per inch) and 256 levels of gray, recorded in the TIFF format without compression. In order to achieve a higher degree of reliability for the results, IIW *(International Institute of Welding*) radiographic standards were used[1], totaling 86 films containing the main defect classes: lack of penetration, undercutting, porosity, inclusion, crack, etc.

Preprocessing the Radiographic Images

After digitizing the films, it is common practice to adopt a preprocessing step for the images with the special purpose of reducing/eliminating noise and improving contrast. This procedure allows one to obtain an image that makes identification of welding defects that might be present in the welding bead easier. The use of low pass filters is the most utilized tool to soften noise in a radiographic image[9-10]. Radiographic images show substantial variation depending on the testing technique adopted as well as the material being inspected, which makes it difficult to choose a standard filter for noise elimination. Therefore, the right choice is normally made empirically, bearing in mind that use of these filters must not alter the relevant information on those images. Some authors, like Aoki[2], resort to applying other procedures such as *Background Subtraction* and segmentation by *Region Growing Method* to facilitate defect identification.
Two preprocessing steps were carried out in this project: application of a median type low pass filter and contrast improvement by extending the image's histogram. Implementation of these steps was performed with the software *Image Pro Plus 4.0* (Media Cybernetics).

Definition of the Characteristic Parameters for the Defects

One of the most important steps in designing a radiographic inspection automated system is defining the characteristic parameters for the defects. The proper choice of the most relevant characteristics in identifying each class of defects is extremely important for their process of recognition by the intelligent system. This choice is made in a way similar to the interpretation done by an inspector that, frequently, initially recognizes one type of welding defect on the radiograph based on visual characteristics such as location, shape, length, density (gray level), aspect ratio, etc., in addition to observing the welding circumstances. Therefore, an important study of the defect morphology at the image level is required to optimize the system's

[1] Properly authorized by the *International Institute of Welding*.

performance. Aoki[2] describes a system based on the utilization of 10 parameters for identification of 5 defect classes. Kato[11] worked with 8 parameters for classifying 7 types of defects.
In this project 6 parameters were defined to discriminate 4 defect classes: slag inclusion (IE), porosity (PO), lack of penetration (FP) and undercutting (MO). The amount of data utilized consisted of 15 observations for undercutting, 14 for lack of penetration, 17 for porosity and 49 for slag inclusion. Although there were radiographic patterns relating to the classes lack of fusion and crack, these defects were not analyzed because enough data were not available to allow generalization of the classifiers. Figure 1 below shows a flow chart of the principle that was used to choose the parameters. Figure 2 shows an example of an IIW radiographic standards, as well as the dimension measurements necessary to calculate each parameter.

Definition of the utilized parameters:

(1) Contrast (C): ratio between the variation in ash level in the defect (difference between the maximum and the minimum values) and the variation in gray level present in the radiographic image. This parameter was chosen because each defect class has its own degree of density.
(2) Position (P = h/H): this ratio provides the location of the defect relative to the center of the bead. This parameter allows separating lack of penetration, which is frequently located on the center of the bead, from undercutting, that normally occurs on the edge[2, 6].
(3) Aspect ratio (a = L/e): this parameter is used to separate the more spherical classes (pore), where values are in the vicinity of 1, from the less spherical (lack of penetration and linear inclusion), with **L** being the longer axis of the smallest ellipse that surrounds the defect, and with **e** as the smaller axis.
(4) Ratio between width and area (e/A): ratio between the smallest transverse length of the defect and its area. This information quantifies the degree of circumference in the defect[2].
(5) Ratio between length and area (L/A): ratio between the largest horizontal length of the defect and its area. In this parameter **L** does not represent the longer axis of the ellipse. This information quantifies the degree of circumference in the defect[2].
(6) *Roundness* (R): Measures the $p^2/4\pi A$ ratio, where p is the perimeter and A is the area of the defect. From the relation it is observed that when the defect's shape approaches a circumference, this measure will tend to 1, which is useful to separate spherical classes like porosity and non-linear slag inclusion, from the linear lack of penetration, linear inclusion and undercutting.

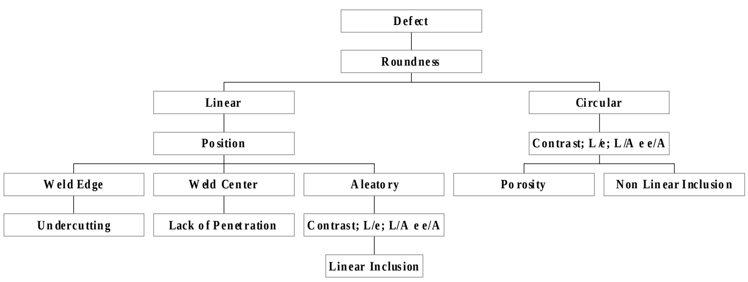
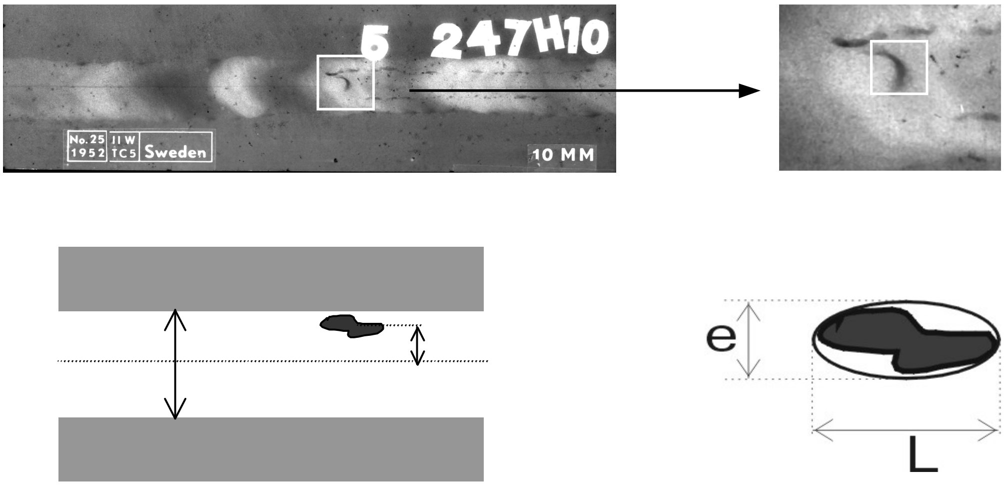


Figure 1: Flow chart representing the separation of defect classes by means of the utilized parameters.



(c) (d)

Figure 2: (a) Example of a utilized IIW standard; (b) presence of slag inclusion; (c) and (d) illustration for defining the utilized parameters.

Parameter Evaluation by Linear Correlation Matrix

The six chosen parameters were correlated among themselves and with the defect classes: slag inclusion, porosity, lack of penetration and undercutting. The correlation between parameters and each defect class was evaluated by analyzing the linear correlation coefficient, well known in statistics and calculated by the formula[12]:

$$C(x,y) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{x_i - \bar{x}}{\sigma_x}\right)\left(\frac{y_i - \bar{y}}{\sigma_y}\right) \qquad (1)$$

$C(x,y)$ - linear correlation between variables ***x*** and ***y***.

$\bar{x}$ and $\bar{y}$ - expected values for variables x and y respectively.

σ_x and σ_y - standard deviations for variables x and y respectively.

Values found for the correlation coefficients are shown in 6×10 matrices (six parameters + four defect classes) to make visualization of results easier. In order to verify the correlation reliability between the parameters or between parameters and defect classes, a criterion was adopted according to which correlation values on the order of $2/\sqrt{N}$, with N being the number of observations of each parameter/class, have 95% probability of indicating an effective correlation between the analyzed data[12].

After determining the parameters most correlated with the defect classes, probably those that are more relevant in the discrimination of a given class, these were de-correlated from the least relevant parameters, according to relation 2 presented below[12].

$$y' = y - \left(\frac{Exy}{Ex^2}\right)x \qquad (2)$$

Exy – expected value for the product between variables.
Ex^2 – expected value for variable ***x*** squared.

After making the de-correlation, a new matrix with the de-correlated parameters was calculated.

Hierarchic Pattern Classifier

The most relevant parameters were used as input data on a hierarchic linear classifier that was designed based on hierarchic linear discriminators optimal for each class. The optimal discriminator is one that maximizes the probability that a classification will be correct. The linear optimal discriminators are a well known technique in statistics called *Fisher's Discriminators*. A practical form of implementing them is by means of a neural network with one layer and, on this layer, the presence of a single neuron per class, as described by Haykin[13]. This technique was used in this project and a detailed description of the hierarchic linear discriminators can be found in Da Silva[14]. The hierarchic classifier operates by initially classifying the most easily separable classes and the algorithm for this classifier is found in [14].

Presentation and Discussion of Results

Table 1 shows the values of correlation coefficients obtained from among the 6 parameters and with the analysis of the 4 defect classes. The rule utilized to verify the existence of correlation follows the ratio $2/\sqrt{N}$. For the parameters, since the total number of data was 95, values higher than (.20) indicate more than 95% probability that correlation occurs (shaded cells). The table also shows the $2/\sqrt{N}$ values for each defect class. A parameter correlation discussion for each defect class will be held based on table 1.

- Undercutting: parameter **P** (position) showed the highest correlation with this class, followed by the **L/A** ratio.
- Lack of penetration: in this class parameters **a**, **R** and **P** showed the highest correlation coefficients.
- Porosity: the **e/A** parameter was the most strongly correlated (.56), followed by parameter **R** (*roundness*).
- Slag inclusion: for this class parameter **P** also showed the highest correlation.

Of these observations, it was concluded that parameter **P** is highly relevant in the discrimination of classes undercutting and lack of penetration, which was something expected since both classes show a very typical and distinct position behavior within the welding bead, with **P** being also relevant in the discrimination of slag inclusion. Since the **e/A** ratio showed high relevance in discriminating porosity, it was observed that parameters **P** and **e/A** were the most relevant in discriminating the classes under study.

From table 1, it was verified that parameters **L/A**, **R** and **a** showed correlation with **P**, as well as **a**, **R** and **C** were correlated with **e/A**. Thus, these parameters were de-correlated, according to equation 2, from **P** and **e/A** respectively.

Table 2 presents the correlation coefficients matrix, obtained with the de-correlated parameters. We can observe that, in this case, only parameters **P** and **e/A** maintained correlation with the defect classes. For this reason these parameters were used as input data on a hierarchic linear pattern classifier.

Results showed a 100% success index for classes undercutting and lack of penetration. With regard to porosity the performance was a 76% success, with 24% of the data being mistaken for slag inclusion. For inclusion, the classifier was right in 85% of the data and mistook 15% for porosity.

In a general performance analysis for this type of classifier having parameters **P** and **e/A** as input data, the correct success index was 88%. This index shows a considerable difference as compared to the 97% of success when the six parameters were utilized for classification of the same defect classes, with the results described in detail in publication[14]. Results showed that the use of these two parameters was sufficient for separating classes undercutting and lack of penetration; however, for porosity and inclusion the performance was inferior when compared to what was obtained with six parameters, in which a 94% of success index was obtained for porosity and 96% was found for inclusion. This discards the possibility of using exclusively these parameters for classifying the 4 classes of defects. Therefore, the hierarchic classifier was tested as well, having three parameters as input data, as follows: **C**, **e/A** and **P,** and **a**, **e/A** and **P**. Parameters **C** and **a** were chosen because, from table 2, it was verified that both would still have some small correlation with the class slag inclusion. For these two conditions, the general correct success index did not change, maintaining the same 88% obtained with **e/A** and **P**. The inclusion of **a** as input data together with **e/A** and **P**, solved the problem of correct matching for the class porosity, because a 100% success index was obtained for that class, whereas for slag inclusion the success percentage became lower as compared to the conditions that had **e/A** and **P,** or **C**, **e/A** and **P** as input data. For this reason, a new input was created with four parameters: **C**, **a**, **e/A** and **P**. In this instance, a 100% of success was obtained for the classes undercutting, lack of penetration and porosity, and 85% of success for slag inclusion, with 15% mistaken for slag inclusion. The general percentage of success was 94%, quite close to the 97% obtained with six parameters[14].

In view of this result, the use of a smaller number of parameters for classifying these 4 defect classes can be discussed. Although the general percentage of success is higher for a larger amount of employed parameters, it is known that the extraction of these parameters from the radiographic images is not an easy task, normally also leading to the occurrence of an error in the measurement process. Consequently, the question arises about finding out what the best cost/benefit relation should be, that is, obtaining the best success index in the most practical way possible.

In terms of bibliographic review, the only paper found that deals with the study of characteristic parameters for classifying welding defects is the one by Aoki[2]. Aoki[12] evaluated the relevance of 10 parameters to discriminate the defect classes undercutting, lack of penetration, porosity, slag inclusion and crack, arriving at the conclusion that the network's performance decreased when a parameter would be removed as input data. However, Aoki[2]

utilized a non-linear classifier (neural network with 3 layers), and he did not resort to the linear correlation coefficients.
It is important to highlight that the defect classes crack and lack of fusion, very frequently found in welded joint radiographs, were not studied in this project because of a lack in the quantity of available standards. This is going to be addressed in future studies.

Table 1. Correlation matrix with correlated parameters.

Characteristic Parameters							Defects			
$2/\sqrt{N}$	**0.20**						**0.28**	**0.48**	**0.53**	**0.51**
	C	**a**	**L/A**	**e/A**	**R**	**P**	**IE**	**PO**	**FP**	**MO**
C	1.00						0.19	-0.30	-0.02	0.08
a	0.15	1.00					-0.07	-0.38	0.50	0.02
L/A	-0.19	0.03	1.00				0.28	0.06	-0.02	-0.44
e/A	-0.23	-0.53	0.60	1.00			0.06	0.56	-0.34	-0.33
R	0.13	0.78	0.14	-0.50	1.00		0.02	-0.42	0.46	-0.04
P	-0.06	-0.16	-0.39	-0.14	-0.24	1.00	-0.34	0.11	-0.48	0.82

Table 2. Correlation matrix with de-correlated parameters.

Characteristic Parameters							Defects			
$2/\sqrt{N}$	**0.20**						**0.28**	**0.48**	**0.53**	**0.51**
	C	**a**	**L/A**	**e/A**	**R**	**P**	**IE**	**PO**	**FP**	**MO**
C	1.00						0.20	-0.18	-0.10	0.01
a	0.01	1.00					-0.15	-0.06	0.24	0.03
L/A	-0.10	0.36	1.00				0.16	0.11	-0.22	-0.12
e/A	0.00	0.00	0.60	1.00			0.06	0.56	-0.34	-0.33
R	-0.02	0.66	0.46	0.00	1.00		-0.07	-0.11	0.16	0.05
P	-0.10	0.00	0.00	-0.14	0.00	1.00	-0.34	0.11	-0.48	0.82

Conclusions

In order to optimize the classification of defects, it is important to have a knowledge of the classifier's input data, especially with the purpose of working with information relevant to the classification process, discarding data that will not contribute in any way toward the system's performance.
The evaluation of characteristic parameters following a relevance criterion in discriminating welding defect classes by using a linear correlation coefficients matrix is innovative, and has demonstrated to be very promising.
The results obtained in terms of success index, when the quantity of parameters used as the classifier's input data was reduced, using only the most relevant, are very close to those obtained with six parameters[14].
However, future studies will be carried out to evaluate not only other characteristic parameters, but also the influence they have in discriminating the classes crack and lack of fusion.

References

(1) Aoki K., Suga Y., “Intelligent Image Processing for Abstraction and Discrimination of Defect Image in Radiographic Film”, *Proceeding of the Seventh International Offshore and Polar Engineering Conference*, Honolulu, USA, may 25-30, 1997, pp. 527-531.
(2) Aoki K., Suga Y., “Application of Artificial Neural Network to Discrimination of Defect Type Automatic Radiographic Testing of Welds”, ISI International, vol. 39, No.10,1999, pp.1081-1087.
(3) Liao T.W., Ni J., “An Automated Radiographic NDT System for Weld Inspection: Part I – Weld Extraction”, NDT&E International, vol. 29, No.3, 1996, pp.157-162.
(4) Liao T.W., Ni J., “An Automated Radiographic NDT System for Weld Inspection: Part II – Flaw Detection”, NDT&E International, vol. 31, No.3,1998, pp.183-192.
(5) Liao T.W., Li D. and Li Y., “Extraction of Welds from Radiographic Images using Fuzzy Classifiers, Information Sciences”, vol.126, 2000, pp. 21-40.
(6) Jacobsen C., Zscherpel U. and Nockemann C., “Crack Detection in Digitized Radiographs with Neuronal Methods”, 7th *European Conference on Non-Destructive Testing*, Copenhagen, 26-29 may, 1998, pp. 2717-2724.
(7) Jagannathan H., Bahaskar N et, “A Step Towards Automatic Defect Pattern Analysis and Evaluation in Industrial Radiography using Digital Image Processing”, *15th World Conference on Non-Destructive Testing*, Rome, 15-21 October, 2000.
(8) Nafaâ N., Redounane et al, “Weld Defect Extraction and Classification in Radiographic Testing Based Artificial Neural Networks”, 15th *World Conference on Non-Destructive Testing*, Rome, 15-21 October, 2000.
(9) Da Silva R.R, “Images Processing Radiographic and Analysis of Defects in Weld Bead”, Master’s Degree, PEMM/COPPE/UFRJ, April, 1999.
(10) Murakami K., “Image Processing for Nondestructive Testing, Welding International”, vol.4, No.2, pp.144-149, 1998.
(11) Kato Y., Okumura T. and Matsui S. et al, “Development of an Automatic Weld Defect Identification System for Radiographic Testing”, *Welding in the Word*, vol. 30, No.7/8, pp.182-188, 1992.
(12) Chatfield, C., *The Analysis of Time Series – An Introduction*, Chapman and Hall, fourth edition, 1989.
(13) Haykin, S., *Redes Neurais – Princípios e Prática*, Bookman, 2ª edição, Porto Alegre, 2001.
(14) Romeu R. da Silva, Marcio H. S. Siqueira. et al, “Radiographics Pattern Recognition of Welding Defects using Linear Classifiers”, Insight, vol.43, No. 10, October, 2001, pp.669-674.