CLASSIFICATION OF WELDING DEFECTS IN RADIOGRAPHS USING TRAVERSAL PROFILES TO THE WELD SEAM

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Abstract: In patterns recognition applied to welding defects in digitized radiographic images, there are two research fields basically: techniques that involve segmentation, extraction of features and classification of the detected defects, or methods that involve transverse profiles to the weld seams. In this work, we present the results of a study to detect welding defects in radiographs using traverse profiles to the weld seam. The profiles were traced transversely to the weld seam of several radiographic patterns from IIW (International Institute of welding). Later on, the resulting profiles were normalized and pre-processed for noise smoothing. With training and test input sets, selected using techniques of random sampling, the performances of the classifiers, which were implemented using feedforward networks with learning algorithm for error backpropagation, were evaluated. The true accuracy of these classifiers was estimated with base in the results of each set input. Techniques of *principal components of nonlinear discrimination* were also used for two-dimension visualizations of the separation between two classes (Defect and Nondefect). The accuracy results obtained are presented in tables and they were about 80% with test sets.

Introduction: Considering the relevancy of radiographic inspection to many types of industries, there has been having many researches aiming to automate the analysis and interpretation of welding discontinuities in radiographic films for a long time. Generally, these researches are divided into four main steps: digitizing and acquisition of radiographic image, welding seam extraction, detection of discontinuities and, finally, classification and judgment of the discontinuities detected. The first step consists usually on a digitizing of the radiographic film by an image scanner constructed specifically to do it. This device shall provide appropriated resolution. Recently, we already have the digital radiography available to have these images. The welding seam extraction require an algorithm of image processing to extract only the interest area, and them reduce the amount of information and time necessary for subsequent steps. On the third step, algorithms of pattern recognition are applied in order to detect anomalies on the transversal profile of the radiographic image. These algorithms are applied with intelligent systems that look for discontinuities along the welding. Finally, the classification of defects is carried out by an intelligent system too. The discontinuity detected previously must be recognized among many known types regarding their geometry, location and other features inherent to the image [1-10]. Beyond classification, the discontinuities shall be judged as acceptable or not, according to the Standard or Code applicable.

In this paper, we present the results obtained by a methodology for automatic detection of welding defects. Radiographic patterns of IIW were digitized by using professional scanner. The digitized images were pre-processed to reduce the noise and improve the contrast with median filter and contrast equalization. Then, profiles were transversely traced images out. These profiles were employed as training and test input sets in nonlinear pattern classifiers, which were implemented by artificial neural networks. Techniques of principal components of nonlinear discrimination [7] were also used for two-dimension visualizations of the separation between classes. The present problem of pattern classification involved discrimination between two classes: *profiles without defect* (ND) and *profiles with defect*s (D), including: undercut (UC), incomplete penetration (IP), lack of fusion (LF), pore (PO), slag inclusion (SI) and crack (CR). The accuracies of these classifiers were estimated by random sampling of the input set and the results obtained are presented in tables. The estimated accuracies were up to 80% for test sets, which can be considered has a successful performance regarding the number of samples used and the classification complexity involved in this system.

- ***Radiographic Patterns and Film Digitalization***

Although there are scanners such as the Agfa RADView FS 50, ideal for high-density films, due to the high quality of the films, a low-cost scanner, a UMAX, Mirage II model (3.0 maximum optical density; with 2000 dpi of maximum resolution for films) was used for the digitalization of the radiographs, following the ASME Code Sec. V. The resolution employed was 500 dpi (dots per inch), giving an average size (due to a small variation in the film sizes) image of 2,900 pixels (horizontal length) × 950 pixels (vertical length), which resulted in an average pixel size of 50µm. This resolution was adopted as it permitted the detection and measurement of defects of sizes in the order of hundredths of an mm, which in practical terms of radiographic inspection is well above normal. The resolution in tones of gray chosen was eight bits (256 levels).

- ***Pre-processing of Gray level Profiles***

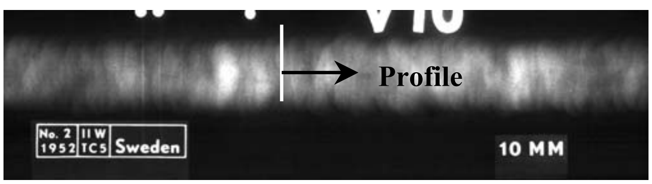
Gray level profiles transversal to weld seam was extracted from radiographic images. Each profile is considered as a signal. The system involved 2 classes of signals, nondefects (ND) and defects (D). The input set had 1400 signals (200 signals without defects and 1200 with defects). Firstly, a smoothing was carried out with the filter Savitzky-Golay [11]. The best condition of smoothing was found using 8 points in the window size and a second order function. Originally, profiles were different in number of points due to variation in resolution of images and width of weld seams. Then, smoothed profiles were interpolated using FFT (Fast Fourier Transform) method [12] in order to have all profiles with the same dimension (number of points). Figure 1 shows two examples of profiles extracted from radiographic patterns, with and without defect. After smoothing, it was noted that location of defect is important for classifier performance. As normalization of the data concerning to defect positions, some profiles were inverted in order to obtain all defects at the right side of the center of the Gaussian curve fitted from the smoothed profiles, as far as Liao [2-4] showed that this transversal signal present a shape similar to Gaussian curve. The right side of Gaussian curve was chosen only to normalize all signals, i.e., there is no specific reason.

- ***Nonlinear Classifiers***

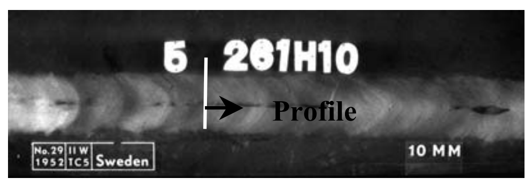
Nonlinear classifiers were implemented with two layers neural network, backpropagation of error was used as training algorithm [13-14]. The number of neurons in hidden layer was worked out to provide the best results for tests, aiming to improve generalization capability of classifier. Some neural network parameters was tested and adjusted to make training faster and improve its performance. Training of classifiers was done with moment (β=0.9) and α variable what provided a faster convergence during training. Normally, training stopped at 3000 epochs, when learning errors are stabilized.

- ***Principal Components of Nonlinear Discrimination***

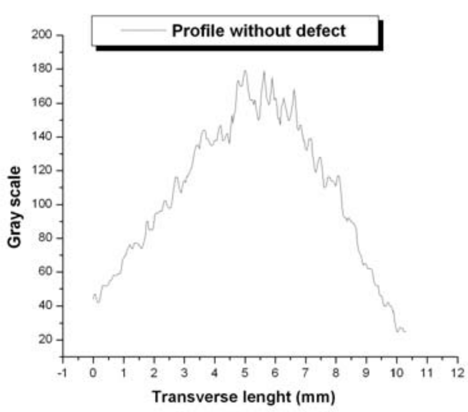
The calculation of principal components is very useful, because they provide a data distribution in a bi-dimensional plot. In addition, it's a technique to reduce data dimension. In this work, two independent principal components of nonlinear discrimination were obtained from a three layer neural network; in which the first layer contains only one linear neuron, as described on [6-7]. Two-dimensional plots, composed by two principal components of nonlinear discrimination, were obtained to the classification of the two classes: Defect (D) and Nondefect (ND). Figure 1 show this plot for two classes.



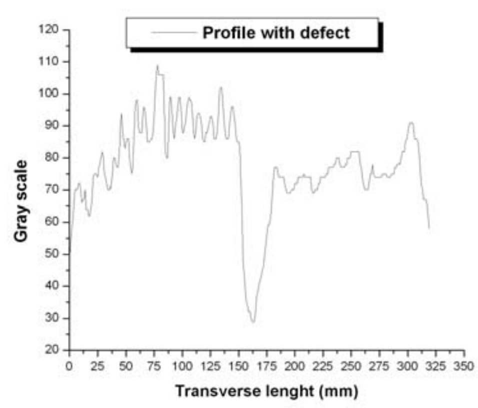
Radiography without defect.



Radiography with incomplete penetration.



(a)



(b)

FIGURE 1: Examples of a grayscale profile without defect (a) and with incomplete penetration (b).

- ***Estimated Accuracy of Classifiers***

There are various techniques to estimate the accuracy of a classifier, but basically there are three that are the most used: simple random selection of samples, cross validation that presents diverse implementations [15], and the *bootstrap* technique [16-17]. Actually, it is not possible to confirm whether one method is better than the other for any specific pattern classification system. The choice of one of these techniques will depend on the quantity of samples available and the specific classification to be made. To calculate the accuracy of the detection (classification between the two classes: profiles with defect (D) and profiles without defects (ND)), random sampling was applied to the each original input set in order to produce the training and test sets. The original set was divided into 80% for training sets and 20% for test sets. The training group was divided into two groups, 90% for training and 10% for validation in order to assure the classifier reliability. It was carried out ten times and the estimated accuracies were calculated by average of the performance sets.

Results:

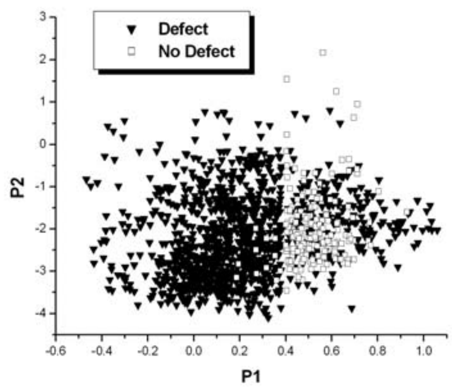


FIGURE 2: P1 x P2 nonlinear for the two classes: Defect and Nondefect.

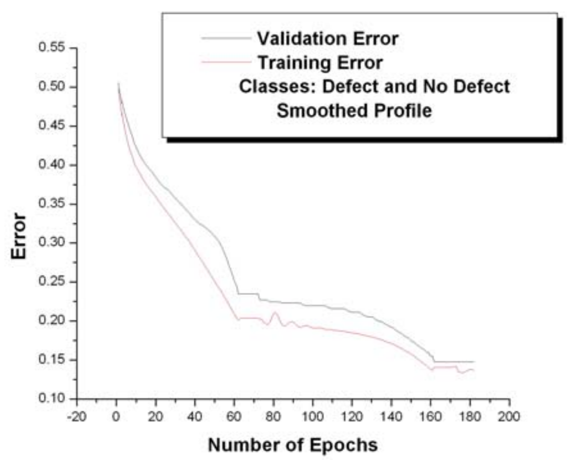


FIGURE 3: Error curve, demonstration of stop criteria.

TABLE 1: Variation of the number of neurons in the intermediate layer and the performances obtained for the training and test sets in the defect detection (smoothed profiles; two classes: with and without defect).

Number of Neurons	Training	Test
5	99.55	91.07
7	99.91	93.57
9	99.20	91.43
11	99.55	95.00
13	99.64	93.21
15	**99.82**	**96.07**
17	100.00	93.21
19	99.46	94.29
Maximum	100.00	96.07
Minimum	99.20	91.07

TABLE 2: Performance of classifier for 10 random groups (15 neurons; smoothed profiles; two classes: with and without defect).

Group	Training	Test
1	94.20	73.81
2	81.76	65.71
3	90.76	71.90
4	92.18	70.95
5	91.51	71.43
6	92.44	70.95
7	93.11	78.10
8	92.77	77.14
9	91.93	77.62
10	91.85	75.24
Media	**91.25**	**73.29**
Standard Deviation	**3.46**	**3.86**
Maximum	94.20	78.10
Minimum	81.76	65.71

TABLE 3: Variation of the number of neurons in the intermediate layer and the performances obtained for the training and test sets in the defect detection (smoothed and inverted profiles; two classes: with and without defect).

Number of Neurons	Training	Test	Difference
5	99.73	95.00	4.73
7	99.91	95.71	4.20
9	99.91	94.64	5.27
11	99.82	93.57	6.25
13	**99.46**	**96.43**	**3.04**
15	100.00	95.00	5.00
17	99.73	96.43	3.30
19	99.46	95.71	3.75
21	99.73	94.29	5.45
Maximum	100.00	96.43	
Minimum	99.46	93.57	

TABLE 4: Performance of classifier for 10 random groups, smoothed and inverted profiles, 13 neurons (two profile classes: with and without defect).

Group	Training	Test
1	99.73	94.64
2	99.46	87.86
3	99.46	93.21
4	99.73	89.64
5	99.02	78.93
6	85.89	85.71
7	100.00	86.07
8	98.21	86.43
9	99.82	88.93
10	99.91	88.57
Media	**98.13**	**88.00**
Standard-Deviation	**4.33**	**4.33**
Maximum	100.00	94.64
Minimum	85.89	78.93

Discussion: Figure 2 shows a plot of two principal components of linear discrimination obtained by a nonlinear classifier, implemented by three layer network. The first layer contains only one linear type neuron, others hiperbolic tangent type [7]. The plot of principal components allowed a two dimensions view of separation level between Nondefect and Defect classes. They presented a considerable separation level in this bi-dimensional space, even when classification errors are considered for both classes. However, in practice, more than two discrimination components can be used to identify both classes. In this work, these components were not used as input of classifiers, aiming to reduce dimension of files. It will be accomplished in future works.

This type of hierarchic classification was used by Silva [5] and will be studied for future implementation. The next step was to study the best number of neurons in intermediate layer of classifier to detect detects.

Figure 3 shows the error curve, where we can observe that stop criteria intend to minimize difference between training and validation error in order to control the over fitting of the classifier.

Tables 1 show the performance of training/test sets for smoothed signal, previous normalization regarding to defect position. Table 2 the performance of nonlinear classifier with 15 neurons. The performance of classifier was improved a lot after inversion of some profiles, as discussed below.

Table 3 show the performance of a training/test sets, where number of neurons in intermediate layer was varied. The choice of training/test group was accomplished to guarantee the same percentage of defects (1200) and nondefects (200) profiles, i.e., 960 profiles of defects for training and 240 for test, 160 profiles of nondefects for training and 40 for test. According to table 3, the success percentage increases from 5 to 21 neurons, the best performance of test was observed with 13 neurons in intermediate layer. Since the quantity of samples was small, principally for nondefects profiles, validation groups were not created during training as usual to overtraining control. However, the number of neurons control in intermediate layer allows reducing probability of network parameters overtraining. Generally, the number of neurons is adjusted to perform the smallest difference between results of training and test, what occurred with 13 neurons in intermediate layer in this case. This reduction on number of neurons at intermediate layer was possible after performing the inversion of smoothed signal. Since processing the same group of smoothed signal without any inversion of profile was done previously, as described above. A great improvement of network performance was reached with normalization of defect position.

Table 4 shows the performance of nonlinear classifier with 13 neurons. Standard-deviation found was low enough to guarantee a successful system of welding defects detection, since among 10 groups only one was found to be below 98% for training and 85% for test. It's a good result if we consider that most experience group of inspectors distinguishes correctly 90% defects from nondefects [18-19].

Conclusions: From results presented above, we can conclude as follows:

- Pre-processing of profiles prior submitting to classifier is very important for successful detection system, not only to smooth noises from the profiles, but to normalize the defect position.
- Normalization of defect position regarding to one side of center of Gauss fitted curve provides a great improvement on classifier performance.
- Nonlinear classifier implemented by neural network provides a good accuracy on detection of welding defects from transversal profiles to weld seams.
- This work must continue in order to turn this system able to discriminate the main type of welding defects detected.

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References:

1. A. Kehoe, G.A. Parker "Image Processing for Industrial Radiographic Inspection: Image Enhancement". British Journal of NDT 1990; Vol.32 N.4. pp. 183-190.
2. T.W. Liao, K. Tang "Automated Extraction of Welds from Digitized Radiographic Images Based on MLP Neural Networks". Applied Artificial Intelligence 1997. vol.11.pp 197-218.
3. T.W. Liao, Y. Li "An Automated Radiographic NDT System for Weld Inspection: Part II – Flaw Detection". NDT&E International 1998. Vol.31. N.3.pp. 183-192.
4. Wang, G, Liao, T. W. Automatic Identification of Different Types of Welding Defects in Radiographic Images. NDT&E International 2002; 35: 519-528.
5. R. R. Silva, M.H.S. Siqueira, L.P. Calôba, et al. "Radiographics Pattern Recognition of Welding Defects using Linear Classifiers". Insight 2001. Vol. 43. N.10: 669-674.
6. R.R Silva et al. "Patterns Nonlinear Classifiers of Weld Defects in Industrial Radiographs". 3rd PANNDT. June 2003. Rio de Janeiro. Brazil.
7. R. R. Silva, Calôba L P, Siqueira M.H.S, Rebello, J.M.A. Pattern Recognition of Weld Defects Detected by Radiographic Test. NDT&E International, 2004.
8. G.X. Padua et al "Detection of Welding Defects on Radiographic Patterns Using Artificial Neural Networks". 3rd PANNDT. June 2003. Rio de Janeiro. Brazil.
9.Shafeek, H.I, Gadelmawla, E., Abdel-Shafy, A.A, Elewa, I.M. Automatic Inspection of Gas Pipeline Welding Defects Using an Expert System. NDT&E International, 2004.
10. Shafeek, H.I, Gadelmawla, E., Abdel-Shafy, A.A, Elewa, I.M. Assessment of Welding Defects for Gas Pipeline Radiographs Using Computer Vision. NDT&E International, 2004.
11. J.O. Sophocles. "Introduction to Signal Processing". Prentice-Hall.1995.
12. Curve Fitting Toolbox –For use with MATLAB. User's Guide, Version 1. The Mathworks.
13. S. Haykin ."Neural Networks – A Comprehensive Foundation". Macmillian College Publishing. Inc. 1994.
14. C.M. Bishop. "Neural Networks for Pattern Recognition". New York. Oxford University Press. 1995.
15. Diamantidis, N.A., Karlis, D., Giakoumakis, E.A. Unsupervised Stratification of Cross-Validation for Accuracy Estimation. Artificial Intelligence 2000. 116: 1-16.
16. Efron, B., Tibshirani, R. J. An Introduction to the Bootstrap. New York, Chapman & Hall/CRC, 1993.
17. Efron, B., Tibshirani. Cross-Validation and the Bootstrap: Estimating the Error Rate of the Prediction Rule. Technical Report 477, Stanford University 1995. http://utstat.toronto.edu/tibs/research.html.
18. F. Fucsok, M. Scharmak. Human Factors: The NDE Realibility of Routine Radiographic Film Evaluation. In: 15th World Conference on Non-Destructive Testing. Rome, October 15-21 2000.
19. F. Fucsok, C. Muller, M. Scharmak. Reliability of Routine Radiographic Film Evaluation – An Extended ROC Study of the Human Factor. In: 8th European Conference on Non Destructive Testing. Barcelona, June 17-21 2002.