AN AUTOMATIC WELDING DEFECTS CLASSIFIER SYSTEM

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Abstract: Radiographic inspection is a well-established testing method to detect weld defects. However, interpretation of radiographic films is a difficult task. The reliability of such interpretation and the expense of training suitable experts have allowed that the efforts being made towards automation in this field. In this paper, we describe an automatic detection system to recognise welding defects in radiographic images. In a first stage, image processing techniques, including noise reduction, contrast enhancement, thresholding and labelling, were implemented to help in the recognition of weld regions and the detection of weld defects. In a second stage, a set of geometrical features which characterise the defect shape and orientation was proposed and extracted between defect candidates. In a third stage, an artificial neural network for weld defect classification was used under three regularisation process with different architectures. For the input layer, the principal component analysis technique was used in order to reduce the number of feature variables; and, for the hidden layer, a different number of neurons was used in the aim to give better performance for defect classification in both cases. The proposed classification consists in detecting the four main types of weld defects met in practice plus the non-defect type.

1 INTRODUCTION

In the last five decades, Non Destructive Testing (NDT) methods have gone from being a simple laboratory curiosity to an essential tool in industry. With the considerable increase in competition among industries, the quality control of equipment and materials has become a basic requisite to remain competitive in national and international markets. Although it is one of the oldest techniques of non-destructive inspection, radiography is still accepted as essential for the control of welded joints in many industries such as the nuclear, naval, chemical, aeronautical. It is particularly important for critical applications where weld failure can be catastrophic, such as in pressure vessels, load-bearing structural members, and power plants (Edward, 1993).

For the correct interpretation of the representative mark of a heterogeneity, a knowledge of welded joint features and of the potential heterogeneities and types of defect which can be detected using radiographic welded joint inspection is necessary. Limitations to correlating the heterogeneity and the defect are imposed by the nature of the defect (discontinuities and impurities), morphology (spherical, cylindrical or plain shape), position (superficial or internal location), orientation and size. Therefore, the radiographic welded joint interpretation is a complex problem requiring expert knowledge.

2 EXPERIMENTAL METHOD

Figure 1 shows the major stages of our welding defect detection system. Digital image processing techniques are employed to lessen the noise effects and to improve the contrast, so that the principal objects in the image become more apparent than the background. Threshold selection methods, labelled techniques and feature extraction are used to obtain

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a feature discriminatory that can facilitate both the weld region and defects segmentation. Finally, features obtained are input pattern to artificial neural network (ANN). Previously, principal component analysis (PCA) is first used to perform simultaneously a dimensional reduction and redundancy elimination. Secondly, an ANN is employed for the welding fault identification task where three regularisation process are employed in order to obtain a better generalisation.

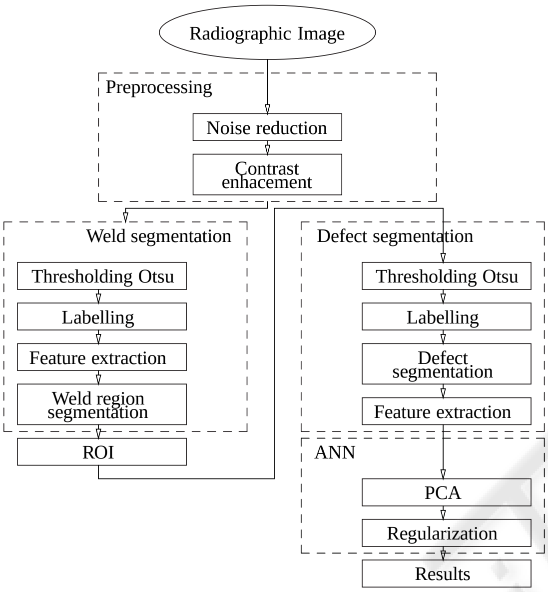

Figure 1: Procedure for the automatic welding defect detection system.

After digitising the films (Zscherpel, 2000; Zscherpel, 2002), it is common practice to adopt a preprocessing stage for the images with the specific purpose of reducing/eliminating noise and improving contrast. Two preprocessing steps were carried out in this work: in the first step, for reducing/eliminating noise an adaptive Wiener filter (Lim, 1990) and Gaussian low-pass filter were applied, while for adjusting the image intensity values to a specified range to contrast stretch, contrast enhancement was applied in the second step.

The last stage is the feature extraction in terms of individual and overall charcateristics of the hetereogeneities. The output of this stage is a description of each defect candidate in the image. This represents a great reduction in image information from the original input image and ensures that the subsequent classification of defect type and cataloguing of the degree of acceptance are efficient. In the present work, features describing the shape, size, location and intensity information of defect candidates were extracted.

The dimension of the input feature vector of defect candidates is large, but the components of the vectors can be highly correlated and redundant. It is useful in this situation to reduce the dimension of the input feature vectors. An effective procedure for performing this operation is principal component analysis. This technique has three effects: it orthogonalises the components of the input vectors (so that they are uncorrelated with each other), it orders the resulting orthogonal components (principal components) so that those with the largest variation come first, and it eliminates those components that contribute the least to the variation in the data set.

3 MULTI-LAYER FEED-FORWARD ANN

A multiply-input neuron model is shown on the left in Figure 2. The topology of the network used in this work is illustrated on the right in Figure 2. Nonlinear pattern classifiers were implemented using ANNs of the supervised type using the error backpropagation algorithm and two layers, one hidden layer (S_1 neurons) using hyperbolic tangent sigmoid transfer function and one output layer($S_2 = 5$ neurons) using a linear transfer function. In this work, a BFGS algorithm (Dennis and Schnabel, 1983) was used to train the network. The algorithm requires more computation in each iteration and more storage than the conjugate gradient methods, although it generally converges in fewer iterations. The approximate Hessian must be stored, and its dimension is $n \times n$, where n is equal to the number of weights and biases in the network, therefore for smaller networks can be an efficient training function.

One of the problems that occur during neural network training is called overfitting. The error on the training set is driven to a very small value, but when new data is presented to the network the error is large. The network has memorised the training examples, but it has not learned to generalise to new situations. In this work, three methods was used in order to improve generalisation. The first method for improving generalisation is called regularisation with modified performance function. This involves modifying the performance function, which is normally chosen to be the sum of squares of the network errors on the training set. The second method automatically sets the regularisation parameters. It is desirable to determine the optimal regularisation parameters in an automated fashion. One approach to this process is the Bayesian regularisation (MacKay, 1992) (Foresee and Hagan, 1997). The third method for improving gener-

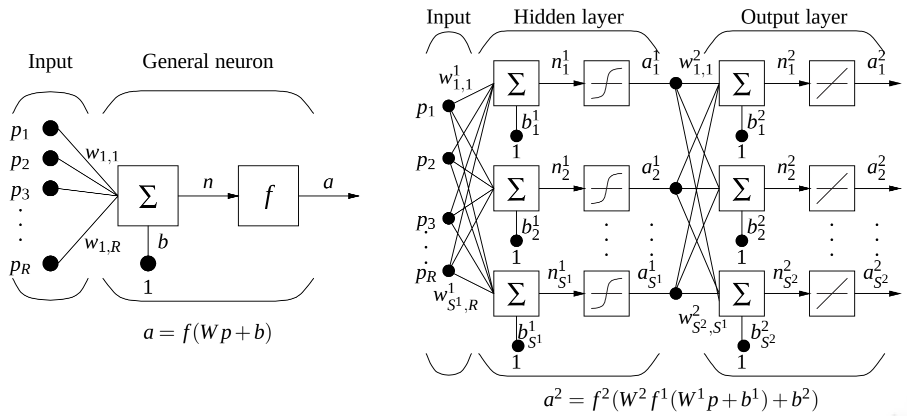

Figure 2: Neuron model and network architecture.

alisation is called early stopping or bootstrap. In this technique the available data is divided into three subsets. The first subset is the training set, which is used for computing the gradient and updating the network weights and biases, in our case 50 % of data. The second subset is the validation set, 25 % of data. The third subset, 25 % of data, is the test set is not used during the training process.

4 RESULTS AND CONCLUSIONS

To validate the proposed technique for the automatic detection of weld defects, the same set of 86 radiograph images from the reference collection of the IIW/IIS were used. In order to evaluate the performance of the system, it is important to know if the system is able to detect all defects. In this stage, our system is able to obtain a sensibility of 100%, i.e. the system detects as defect candidate all the defects observed by the human expert. For a defect detection system it is very important to have minimal loss in defect regions even at the cost of increasing the number of non-defect areas. The performance is obtained with a regression analysis between the network response and the corresponding targets. An artificial neural network can be more efficient if varying the number of neurons R in the input layer (by means of principal component analysis) and S^1 in the hidden layer and observing the performance of the classifier for each defect and for each method of regularisation was possible to obtain the most adequate number of neurons for the input and hidden layer and more appropriate method of regularisation.

Figure 3 illustrates the graphical output of correlation coefficient provided for the regression analysis for each method of regularisation, i.e. using a modified performance function, Bayesian regularisation and stopping early, in average for all classes. In general, all outputs seem to track the targets reasonably very well and all correlation coefficients are rounding 0.8. In some particular case, transversal crack with Bayesian regularisation and stopping early methods for some determined number of PCA variation and hidden layer neurons, the correlation coefficient is not so good. These results are shown in Table 1 for each one of the categories of regularisation and defect types for a better interpretation. Underlined results are the optimum values for our aim.

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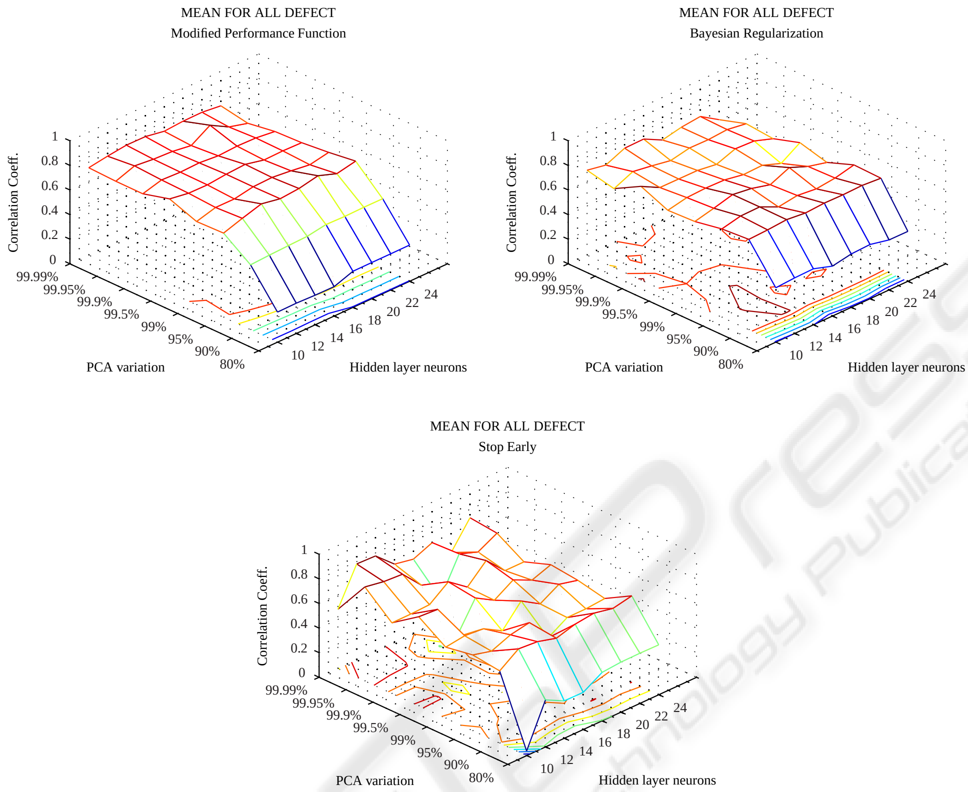

Figure 3: Mean Correlation coefficient for each regularisation method.

Table 1: Better results for correlation coefficients (C.C.) for a specific number of neurons in the input layer (I. n.) and hidden layer (H. n.) for each defect class and for each regularisation method.

		Regularisation Method								
		Mod. perf. func.			Bayes. regress.			Stop. early		
	No defect	0.9209	10	20	0.9042	7	22	0.9209	11	14
D	slag Incl.	0.7055	7	24	0.7209	11	10	0.7013	11	16
e	Poros.	0.7562	10	18	0.7204	7	20	0.7754	11	16
f.	T. Crack	0.7978	11	22	0.8637	7	14	0.8637	11	12
	L. Crack	0.9623	2	22	0.9623	8	20	0.9233	8	10
	Mean	0.8041	11	20	0.7619	8	20	0.7802	11	12
		C.C.	I. n.	H. n.	C.C	I. n.	H. n.	C.C.	I. n	H. n.

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