Application of Back-propagation for defect detection in radiographic images

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Abstract

Industrial radiography has been one of the most popular forms of NDT. With more and more sophisticated transducers available, the quality of radiographic images has been better and better. Eventually however, it is a human expert who looks at the image and gives his verdict regarding the quality of the product being examined. In order to automate this aspect, it is imperative to have an expert system capable of detecting flaws in the test object. Artificial neural networks have often been used as a means of adding intelligence to any system. Artificial Neural Networks analyze data by identifying certain signatures or patterns unique for that data. Co-occurrence matrix features have been used to extract useful information from the image. These features have been used as input to the ANN. It is shown here that co-occurrence matrix features combined with back-propagation paradigm of ANN can identify defective templates from a radiographic image. This paper reports, the use of back-propagation paradigm of artificial neural networks in conjunction with co-occurrence matrix features, as an analyzing system.

Keywords: Radiographic image, defect detection, co-occurrence matrix, ANN, Back-propagation.

Introduction

Industrial Radiography has been one of the most popular techniques employed in defect detection. Increasingly sophisticated imaging techniques have been employed to identify and eliminate even hard to find faults. In spite of advances in imaging, the analysis of these images is largely done by a human expert. In the quest to automate even this aspect, people have focused on Artificial Neural Networks.

One of the major challenges faced in automating the identification is the presence of a number of variables viz. size, shape, texture and so on. This makes the task of defect detection, all the more complicated. Straightforward pattern matching algorithms and other image processing techniques alone cannot handle the plethora of variables. Artificial Neural Networks have often been used as pattern classifiers. Their ability to adapt to a high degree of variations has often been exploited in Pattern recognition. ANNs have been successfully applied towards image segmentation and localization of weld defects seen in X-ray images [1].

ANNs have often been used in conjunction with some pre-processing methods in order to accentuate the image under analysis. These pre-processing techniques are used to either enhance the image under analysis, or to extract additional information from them. In this context, extraction of texture features from images, have largely been attributed to co-occurrence matrices. Co-occurrence matrices give a measurement of how often one gray value will appear in a specified spatial relationship to another gray value in the image [2]. One can extract innumerable features/parameters from co-occurrence matrices. Identification of the right features that is useful for given application is a vital aspect in ensuring superior performance.

In this work, the potential of co-occurrence matrix features coupled with ANN, has been explored. The Neural network was built using the back-propagation paradigm. Certain features extracted from the co-occurrence matrices were applied as input to the neural network. This network was subsequently used to identify defective regions in a radiographic image. The results thus obtained, has been presented in this paper.

Theoretical Background

The radiographic images

The radiographic images contain two kinds of defects often seen in industries namely voids and cracks. In the image shown in fig.1, one can see two prominent voids and a more obscure one, and a single crack. There is a gradual gray scale variation in the image that interferes with the defect detection process.

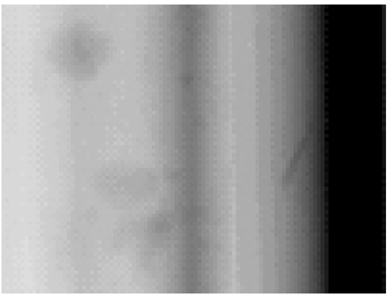

Fig. 1 : Shows the image with void like and crack like defects.

Feature extraction

The process of obtaining more information from a given image is termed feature extraction. There are a wide variety of features one can extract such as histogram features, geometrical features, Fourier transform features, gray level co-occurrence matrix features and so on. In this work, the last method i.e. extraction of features from gray level co-occurrence matrix has been used. A literature survey reveled that co-occurrence matrices are widely and effectively used in texture analysis and segmentation [3].

Gray level co-occurrence matrices carry information regarding the relative position of pixels with respect to each other. It gives the probability of occurrence of a pair of pixels, having a given gray level relationship, in some particular position and orientation specification.

Thus for an image of M rows and N columns, with gray levels defined as i,j for pixel positions (x,y) and ($x+\Delta x$, $y+\Delta y$), where (Δx, Δy) represent the distance and orientation factor, the probability of finding a joint relationship between the above pair of pixels is given by

$$P(i,j)_{xy} = (1/R)*\{\Sigma_{x=1 \mathrm{to} M-\Delta x}\ \Sigma_{y=1 \mathrm{to} N-\Delta y}\ \delta[f(x,y)=i\ \&\ f(x+\Delta x, y+\Delta y)=j]\}$$

$$\delta[\mathrm{false}] = 0 \text{ and } \delta[\mathrm{true}] = 1,$$

$$\text{and } R = (M-\Delta x)*(N-\Delta y)$$

used to normalize the co-occurrence matrix to give probability distribution.

The co-occurrence matrices can be found for different distances and orientations. The distances considered in this work are d=1,2,3. This means the j^{th} pixel is separated from the i^{th} pixel by 1,2,or 3 pixels. The angular orientations considered are 0 deg., 45 deg., 90 deg., and 135 degrees. Thus, co-occurrence matrices were calculated for a combination of above mentioned distances and orientations. Once the co-occurrence matrix is obtained, one can calculate different features such as energy, inverse difference moment, contrast, entropy, diagonal moment, difference variance and so on. After experimentation with different features, only three features namely inverse difference moment, contrast and diagonal moment were used for the analysis [3,4].
The features are calculated as follows

$$\text{Inverse difference moment} = \Sigma_{i=1 \text{ to } 255}\,\Sigma_{j=1 \text{ to } 255}\,[P(i,j)_{xy} * 1/(1+(i-j)^2)]$$

$$\text{Contrast} = \Sigma_{i=1 \text{ to } 255}\,\Sigma_{j=1 \text{ to } 255}\,[\ P(i,j)_{xy} * (\ i-j\ )^2]$$

$$\text{Diagonal moment} = \Sigma_{i=1 \text{ to } 255} \Sigma_{j=1 \text{ to } 255} [\sqrt{ (P(i,j)_{xy} * 1/2 * | i-j |)}]$$

These features are extracted from co-occurrence matrix for four different orientations and three distances.

Artificial Neural Network

Artificial Neural Networks are intelligent systems that once trained, can recognize a pattern in a given data. They are robust towards noise and manage to recognize similarities even in incomplete data set hitherto unseen by the network. There are a number of paradigms developed under ANN, which differ mainly in their training method. One of the most popular paradigms used is the Back-propagation algorithm [5].

Back-Propagation

Back-propagation is a supervised training paradigm. Here, during training the target values are presented at the output nodes and error is calculated. The training is continued till the error comes down to acceptable levels. There are different algorithms employed in back-propagation namely Gradient descent, Levenberg-Marquardt and so on. The basic algorithms are modified for different purposes. In this work, Levenberg-Marquardt algorithm has been used for faster training [5].

Experimentation

Templates of size 14 pixels by 14 pixels were selected from the image. Their co-occurrence matrices were calculated and features were extracted using the formula mentioned above. Images were reconstructed using these features as seen in fig. 2a, fig. 2b, and fig. 2c. The images recreated from the features show a marked difference at the defective regions as against defect less regions as seen from fig 2. It can be seen from fig2a, 2b and 2c that a separation distance of 2 pixels and 3 pixels between the pixel pairs whose joint relationship probability is calculated, gave better distinction as compared to a distance of 1 pixel with respect to defects. Thus, only distance of 2 and 3 were considered. This amounted to a total of 24 gray level co-occurrence matrix features as the input set; 3 features for each of 4 orientations and 2 distances.

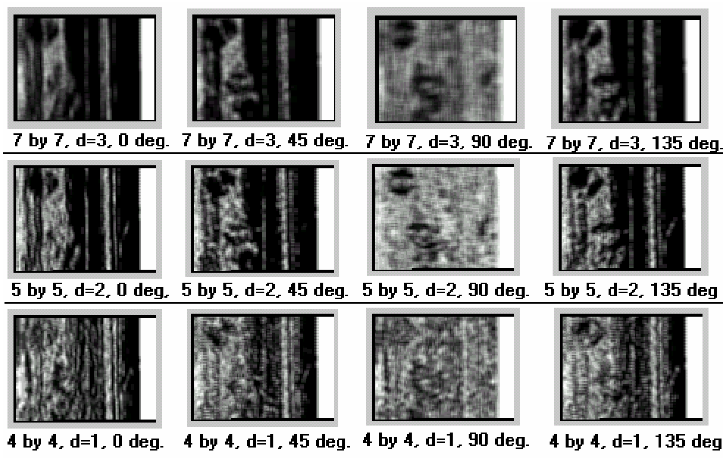

Fig. 2a : shows the inverse difference moment feature for the defective image.

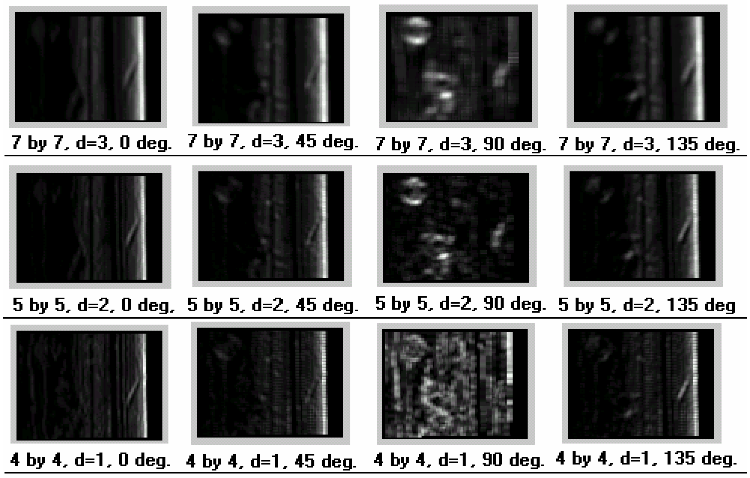

Fig. 2b : shows the contrast feature for the defective image

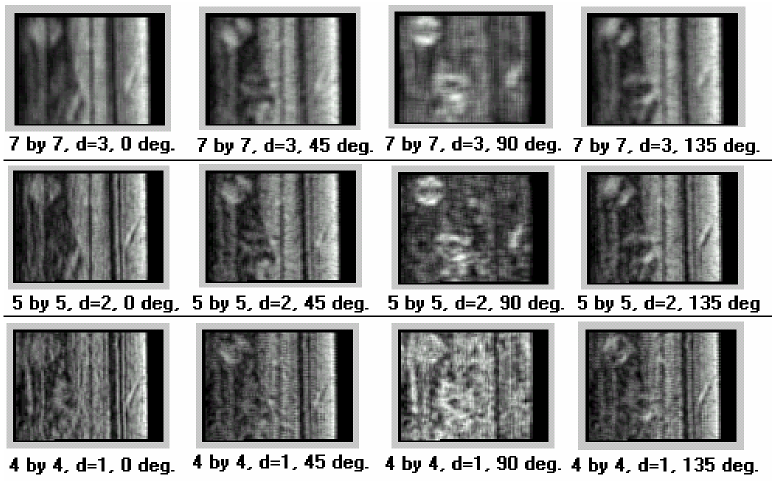

Fig. 2c : shows the diagonal moment feature of the defective image.

From the images it is seen that the features of defective regions are distinctly different from the non defective regions.

These features were given as input to neural network for identification. A back propagation network was used with the following configuration.

- 24 Input nodes representing 24 features obtained from gray level co-occurrence matrix, 5 hidden and 1 output layer node indicating if the template is defective or flawless.
- The activation function used between input and hidden layer was tan-sigmoid (Output between –1 to +1) and the activation function used between hidden layer and output was log-sigmoid (Output between 0 to 1)
- Levenberg-Marquardt algorithm for fast learning was used.
- 200 epochs were used during training.

Fig.3 below shows the identification of the defects after the training stage.

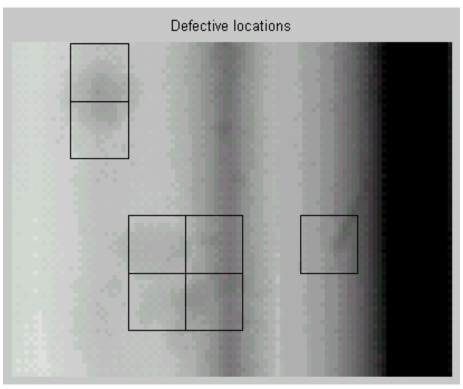

Fig. 3: shows the identification obtained after training.

After training, the network was used to detect defects in other images i.e. in recall mode. For testing the network, images containing only one kind of defect i.e. either voids or cracks were used.

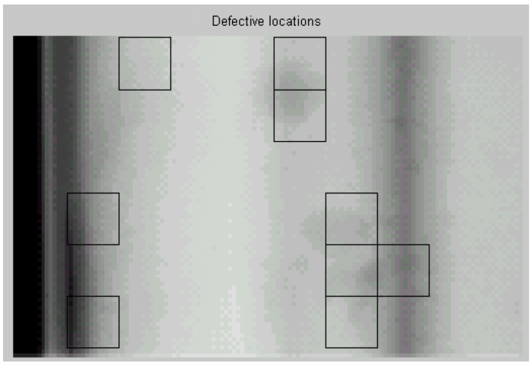

Fig 4a : Test result for spot like defect

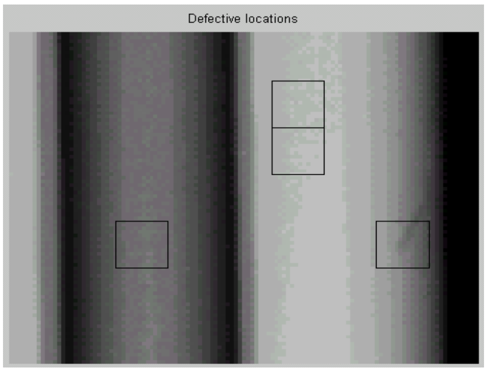

Fig. 4b : Test result for crack like defect

Fig.4a and fig.4b show the testing stage results. It can be seen that the defects have been identified correctly. Also it is seen that there are a few additional false alarms.

Discussion:

The experiments and analysis done in this work, give clear indication that co-occurrence matrix features can effectively bring out more information from radiographic images. These features used in conjunction with artificial neural networks have tremendous potential to form the basis of automatic defect analysis system. Training the network with more images can easily bring down the false alarms seen during the testing stage. Work on this aspect is being presently carried out.

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