Research Journal of Applied Sciences 4 (6): 225-229, 2009
ISSN: 1815-932X

Classification of Stainless Steel Strips Using Artificial Neural Network with Radial Basis Functions

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Abstract: The objective of this study is to design a model based on the artificial neural network with radial basis for automatic classification of stainless steel strips into either good (accepted) or bad (rejected) categories. Firstly, defect is segmented from the background image through optimal thresholding technique and then geometry features such as area and shape complexity of the defect were measured. Artificial neural network structure is employed in the classification stage. The experimental results demonstrate that the proposed method is effective and feasible in stainless steel mills.

Key words: Automatic inspection system, surface defect detection, optimal thresholding, automatic classification, artificial neural network, discriminant function

INTRODUCTION

As the demand of high quality steel increased rapidly quality control of production is then necessary to detect and classified surface defects, which make the product functionally deficient and unusable by customer. Traditionally, the surface quality of stainless steel is inspected manually with human eyes, which will cause many problems, such as subjective results, low efficiency and so on. Automatic inspection systems for metal surfaces have been available for some time to solve these problems. The systems utilized many techniques such as lasers (Quan *et al*., 2000), magnetic leakage, ultrasonic waves (Kehoe *et al*., 2000; Komura *et al*., 2001) and so on. The shortcoming of this issue is online inspection as these techniques are not able to detect defects in real time.

The progress of CCD-sensors to produce grey scale images of the defects and image processing technique has made real time surface defect detection possible online. Several techniques for detecting and classifying defects have been proposed by many researchers by Hao Sun *et al*. (2003), Sugimoto *et al*. (1998), Obeso *et al*. (1997) and Badger and Enright (1996). However, most of the proposed methods are computationally complex and extremely sensitive to illumination changes, camera oscillations, high frequency background objects, biasing of moving objects and the noise coming from the camera. To overcome these problems this study proposed a reliable and robust neural network based algorithms for the classification of stainless steel strips.

MATERIALS AND METHODS

Segmentation and feature selection: The number of surface defect types in stainless steel is large. The most common defect types are inclusion and scales (Suresh *et al*., 1983). Defects are simply extracted from the background by gray level thresholding. The purpose of gray level thresholding is to extract objects pixels from the background of the image. Unfortunately, due to non-uniform lighting, reflection or a number of other factors, which are very frequent circumstances in an image it is inadequate to apply a single threshold to the whole image as a result gray-level variations in objects and background. If a single threshold is not acceptable, then the remaining option consists of using adaptive thresholding, in which the threshold value varies over the image as a function of local image characteristics. There have been many approaches to find this localized thresholding method. The intensity gradient based thresholding methods (Parker, 1991) use the gradient with surrounding pixels as a measure of the decision for the local threshold. Other approaches are based on histogram shape analysis of the image in which the segmentation threshold is determined by statistical method. These approaches have segmentation error disadvantages and can not perform well under variety of image contract conditions. This difficulty is overcome in this study using optimal threshold to maximize gray level variance between defects and background. The optimal thresholding algorithm applied to distinguish defects from the background is as follows:

Algorithm 1: Optimal threshold determination:
Compute μ^t_B, the mean gray level of the corner pixels
Compute μ^t_O, the mean gray level of the object pixels
$T^t = 0$
$T^{(t+1)} = \frac{\mu^t_B + \mu^t_O}{2}$
while $T^{(t+1)} \neq T^t$ do
μ^t_B = mean gray level of pixels for which $f(i, j) < T^{(t+1)}$
μ^t_O = mean gray level of pixels for which $f(i, j) \geq T^{(t+1)}$
$T^{(t+1)} = T^t$
End while

After the thresholding operation which is iterated 8 times, the image data is reduced to the segments of the image which correspond to the edges of the objects of interest, i.e., steel strip detects. Area and shape complexity features of the segmented defects were measured:

- Area-the pixel area of the interior of the object.

Computed as:

$$A = N_o - \left[\frac{N_b}{2} + 1\right] \tag{1}$$

where, N_o and N_b denote, respectively the number of interior and of boundary pixels.

- Shape complexity measure f:

$$f = \frac{A}{\beta^2} \tag{2}$$

Where:
A = The area of the shape
β = The mean distance between the shape internal points and the shape boundary points

Computed as:

$$\beta = \frac{1}{N}\sum d(r,\ boundary(g)) \tag{3}$$

Where:
g = Denote the shape of interest composed of N points, $r \in g$ be a point of g
d (r, boundary (g)) = The smallest distance between r and all boundary points represented by g

The measured features are arranged in form of a pattern vectors of the form $u = (u_1, u_2, ..., u_n)^T$.

Neural network based classification algorithm: Neural network have seen an explosion of interest since their re-discovery as a pattern recognition paradigm in the early 1980s. Neural networks are comprised of many inter-connected group of artificial neurons that uses a mathematical or computational model for data processing. In practical terms, neural networks are non-linear statistical data modeling tools. They can be used to model complex relationships between inputs and outputs or to find patterns in data (Wahyu *et al*., 2006). In this study, Artificial Neural Network with the Radial Basis Function (ANN-RBF), which was trained using a supervised training algorithm was employed. ANN-RBF has one hidden layer of neurons with radial basis activation functions φ (d). A Gaussian function is usually used as a radial basis function:

$$\varphi_j(d) = e^{-\left(\frac{d}{\sigma}\right)^2} \tag{4}$$

Where:
σ = Defines a spread of the Gaussian function and allows adjustment of neuron sensitivity
d = The Euclidean distance between input vector

μ and centers for each data samples c_i in multidimensional space $\Re^n$:

$$d_i = \|\mu - c_i\| \tag{5}$$

Minimizing the Gaussian function with respect to c_i leads to the following conditions:

$$c_i = \frac{\sum_{\mu \in C_i} \mu}{\sum_{\mu \in C_i} 1} \tag{6}$$

The output layer of the ANN-RBF network provides a transformation of a pattern $\mu \in \Re^n$ to an n-dimensional output space. This layer produces discriminant function:

$$\begin{aligned} Y_i = D_i(\mu) = P(C_i/\mu),\quad i = 1,\ 2,\ldots,\ M \\ \approx \sum_{j=1}^{K+1} w_{ij}\varphi_j(d) = w_i^{'}\varphi(d) \end{aligned} \tag{7}$$

where, $w_i = (w_{i1}, w_{i2}, ..., w_{ik}, w_{i,\,k+1})'$ is the weight vector of the ith pattern class and $\varphi(d) = [\varphi_1(d), \varphi_2(d), ..., \varphi_k(d), 1]'$.

With this equivalent formulation we classify input patterns according to the discriminant rule expressed in the form:

$$\begin{aligned} &\text{if } P(C_i/\mu) > \frac{1}{2},\quad \text{assign } \mu \text{ to } C_i \\ &\text{if } P(C_i/\mu) < \frac{1}{2},\quad \text{assign } \mu \text{ to } C_j \end{aligned} \tag{8}$$

The structure of the ANN-RBF automatic classification network using a decision-making process is shown in Fig. 1.

In the Stainless steel strips classification problem three features and decision (discriminant) rule are considered as input-output stimuli's. The radial basis layer generates the decision boundary, which separate the M pattern classes on the basis of the observed measurement vectors which will be used as input-output stimuli's for training of the ANN-RBF network system in support of generating the appropriate classification using the feed-forward algorithm. The error in the network can be calculated as:

$$\varepsilon^k = \frac{1}{2}\sum_{i_o=1}^{M}\left(X_{i_o}{}^k - Y_{i_o}{}^k\right)^2 \tag{9}$$

Where:

$\left(X_{i_o}^k - Y_{i_o}^k\right)^2$ = The square difference between the target output value and actual output value of output layer in the form of class membership of each pattern vector

In order to minimize the error function the partial derivative of the total error with respect to the hidden layer weight w_i is obtain:

$$\begin{aligned}\frac{\partial \varepsilon^k}{\partial w_{ik}} &= \frac{1}{2}\frac{\partial}{\partial w_{ik}}\left[X_{i_O}^k - f\left(\sum_{i_O} w_{i_O}^k\, Y_{i_O}^{kh}\right)\right]^2 \\ &= \left\{Y_{i_O}^k - X_{i_O}^k\right\} \times f\left(\sum_{i_O} w_{i_O}^k\, Y_{i_O}^{kh}\right) Y_{i_O}^{kh} \\ &= \left(Y_{i_O}^k - X_{i_O}^k\right) Y_{i_O}^{kh}\left(1 - Y_{i_O}^k\right) Y_{i_O}^{kh} \\ \frac{\partial \varepsilon^k}{\partial w_{ik}} &= Y_{i_O}^{kO} - Y_{i_O}^{kh}\end{aligned} \tag{10}$$

Where:

$$Y_{i_O}^{kO} = \left(Y_{i_O}^k - X_{i_O}^k\right) Y_{i_O}^{kh}\left(1 - Y_{i_O}^k\right)$$

is the error term from output layer and $Y_{io}{}^{kh}$ is the output from hidden layer. The algorithm performs the updates,

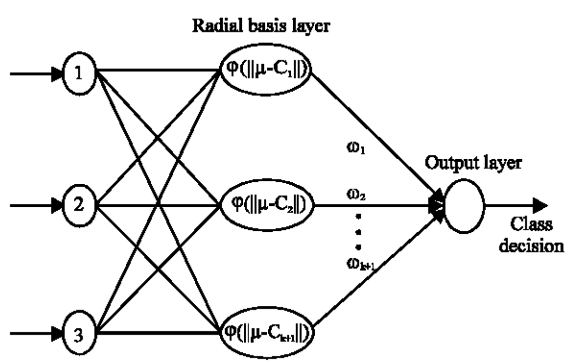


Fig. 1: Structure of the neural network used in decision-making process

$$\Delta w_{i_o}(k+1) = -\beta\sum_{i=1}^{M}\frac{\partial \varepsilon}{\partial w_{i_o}} + \alpha \Delta w_{i_o}(k) \tag{11}$$

iteratively until good performance is obtained (k here counts the iteration of the updates, β is the learning constant and α is the momentum constant). The momentum constant is added to accelerate convergence of the algorithm.

RESULTS AND DISCUSSION

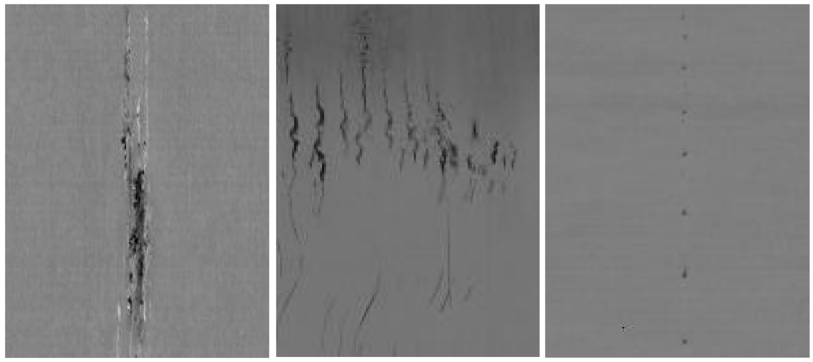
This study begins with the stainless steel's image acquisition and proceeds with the computer guided extraction of surface defects from sample steel strips. Two different kinds of defects are used in this procedure: inclusion and scratches. The choice of these defects type whose sizes range from 0.2 mm and above is based on an analysis of the real defects statistics. To examine the performance of the propose algorithm, laboratory experiments were run on 80 and 90 training stainless steel strips each of sized 500 mm by 800 mm. An example of the defective test images is shown Fig. 2. Two different data set i.e., area and shape complexity features of the occurring defects were measured from all the test sample images and stored in the database.

The experimental results for the network based on two different training data is shown in Fig. 3. This figure generates correct decision boundary between the two classes of training images after 100 iterations. To confirm the effectiveness of the training, the network was tested with four different network configurations. Table 1 shows, setup information and results for each configuration. Each network reached a set of weights capable of correctly classifying the testing images after 100 iterations.

Table 1 is an average over 3 different trials of the experiment. In each trial different database was (randomly) chosen. Graphical representation for the performance analysis of the network is also shown in Fig. 4 and 5. The human experts reevaluated the results from the proposed network to obtain the total percentage of rejections. In the experiment with four different network configurations for the two classes, there is around 1.85% of rejection ratio, which is acceptable in a real industry environment.

Table 1: Results of testing the network

No. of test samples	No. of iterations	Training time (ms)	Correct results (%)	Incorrect results (%)
50	100	9791605	94.0	6.0
70	100	26687798	98.6	1.4
90	100	43549975	100.0	0.0
110	100	86656424	100.0	0.0



(a) Slag inclusion (b) Scratches from pickling line (c) Scratch from cold rolling mill

Fig. 2: Samples of defective stainless steel images

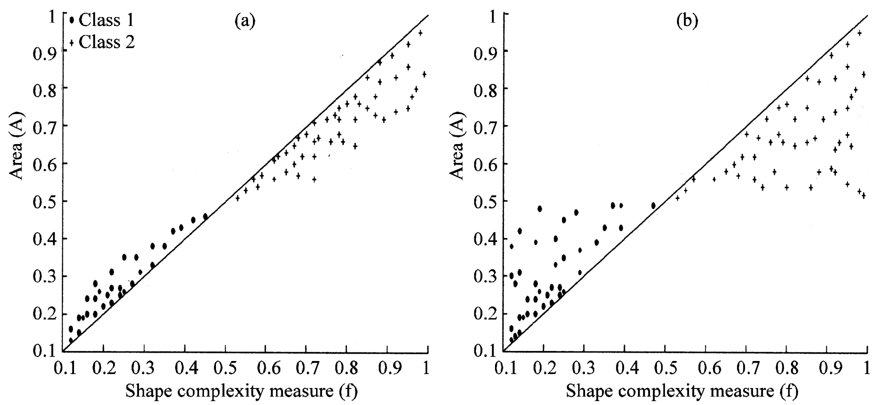


Fig. 3: Classification of stainless steel strips

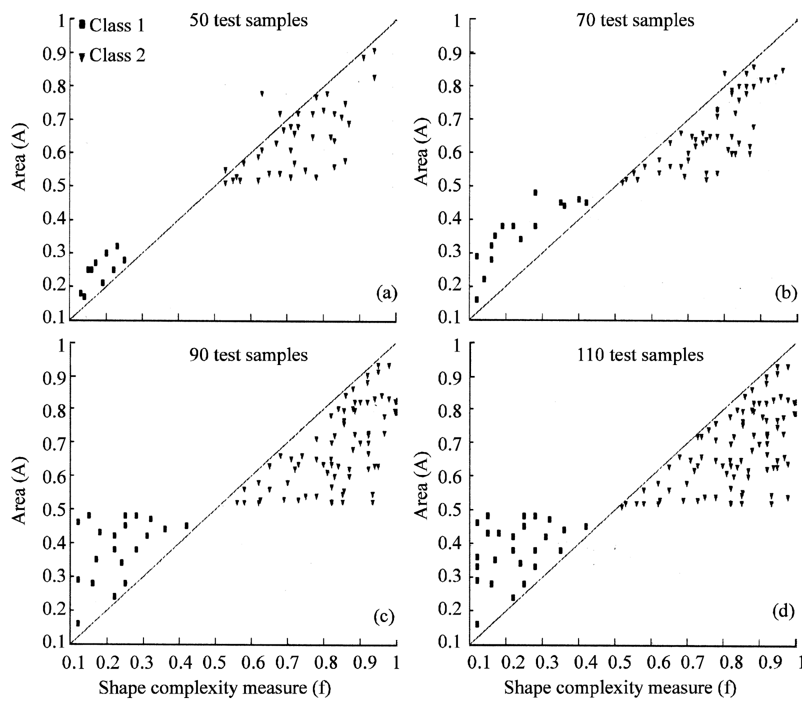


Fig. 4: Classification of test data

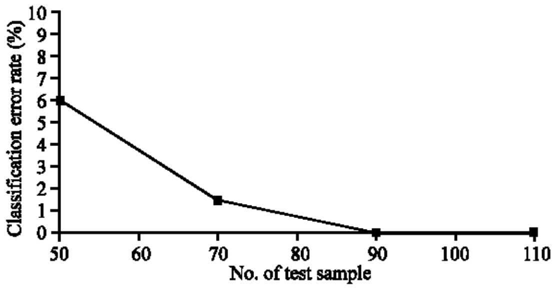


Fig. 5: Effect of test samples on the performance of testing categories

CONCLUSION

A new method has been developed to classify stainless steel strips into good and bad categories according to the complexity of the occurring surface defects. In order to do this a general segmentation methodology and feature selection has been developed. The segmentation methodology has achieved satisfactory results for a great variety of stainless steel strip under changing lighting conditions. The design concept of classifier algorithm discussed in this study is based on mathematical classification rule and ANNs to organize the model database.

Simulation results for the proposed algorithm, which is performed in real time-processing seemed very promising with small error rate of 1.85%.

ACKNOWLEDGEMENTS

The researcher is grateful to Engineer I.A Isaiah at Ladoke Akintola University of Technology, Ogbomoso, Nigeria for his helpful advice.

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