National Conference on Advances in Computer Science and Applications with International Journal of Computer Applications (NCACSA 2012)
Proceedings published in International Journal of Computer Applications® (IJCA)

Laws based Quality Inspection of Steel Productsusing Scanning Electron Microscopy (SEM) Images

B. Sathya Bama
Assistant Professor, ECE Dept
Thiagarajar College of Engg
Madurai

S. Ramabai
Final year ECE
Thiagarajar College of Engg
Madurai

R. Santhanadevi
Final year ECE
Thiagarajar College of Engg
Madurai

ABSTRACT

Since steel is an essential industry raw material and its surface quality is an important evaluation indicator, this paper proposes a quality inspection method for detecting and characterizing defects on steel surfaces. The objective is to detect and classify the defects in the steel products using Scanning Electron Microscopy (SEM) images. In order to obtain better classification accuracy, Discrete Wavelet Transform (DWT) based laws mask method is proposed. Initially, wavelet transform is applied to the input training images and the resultant sub-images are applied with different laws masks like ripple, wave, level, edge and spot. Texture features like mean, entropy, standard deviation, kurtosis and skewness are extracted. The test images are applied with different laws masks and feature values are calculated. These feature values obtained for test and training images are considered for the accuracy assessment which is done based on the minimum distance obtained by taking Sum of Squared Distance (SSD). The accuracy of proposed method is compared with the performance of classical methods namely Tamura features, Gray Level Co-occurrence Matrix (GLCM) and Laws Masks. The overall accuracy of proposed method is 82.5%. The results obtained indicate that better classification of defects is possible by proposed method of applying DWT based laws masks.

Keywords- Scanning Electron Microscopy (SEM), feature extraction, defect classification, accuracy assessment.

1. INTRODUCTION

During the manufacturing process of steel, several kinds of surface defects such as scratch, crack, corrosion, hole, pit and fracture may occur. These flaws not only affect the appearance of the product, even more seriously reduces the corrosion resistance, wear resistance and fatigue properties. In steel strip manufacturing industry, high quality requirements from customers and competitions from steel strip markets make steel strip manufacturers realize the importance of automatic surface inspection system in quality controlling. Mike Muehlemann has analyzed steel quality problems using surface inspections [1]. Laurent Karsenti (2010) has proposed a method for the purpose of defect detection in steel using SEM images [2]. Also tiny defects such as pits which appear to be pseudo defects in steel surfaces are detected and characterized using SEM images [3]. Lee et al (2008) investigated the deformation behaviour of the surface defects with a notch shape on the billet in multi-pass in hot rolling process which focused on the possibility that intentionally produced notches on the billet can diminish or grow when their initial sizes and locations are varied [4]. Shigeru and Kenzo (2005) analyzed stress corrosion cracking in welded parts of the stainless steel using a magnetic non-destructive method [5]. Kuldeep et al (2010) inferred the process knowledge based multi class support vector classification approach for surface defects in hot rolling process [6]. From the survey of all these inspection systems, defect detection process was undertaken only for specific type of defect and defects arising from specific processes. The proposed method detects all type of defects such as corrosion, scratch, cracks and fractures. This paper deals with the advantages of using SEM images instead of ordinary images. Since SEM images have the capacity to magnify micro level variations, they have been used for defect detection purposes. The ultimate objective of this paper is to detect and to classify the different types of defects in the steel structures using different texture based feature extraction techniques and to analyze the efficient method for defect classification.

2. METHODOLOGY

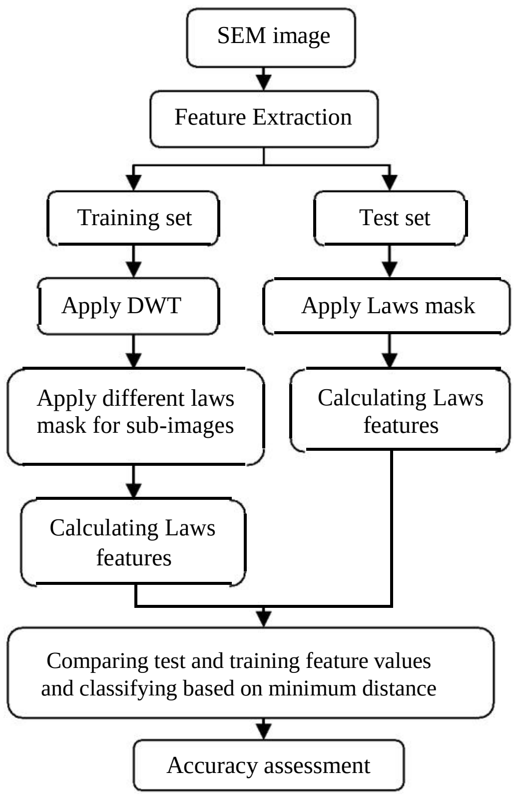


Figure 1. Flow chart for proposed methodology

In this section, an algorithm to detect and classify defects in steel surfaces using Discrete Wavelet Transform (DWT) based Laws masks is proposed. The database used for this method comprises 100 images with different type of defects in steel surfaces namely corrosion, fracture, scratch and crack. Feature extraction of the input steel SEM image comprises two phases (see figure 1).

2.1 Training using DWT with Laws masks

In training phase, the Discrete Wavelet Transform is applied to the input steel SEM image for the known defect. Wavelet transform which is a powerful tool for image analysis have been analyzed by Mallat [7]. This transform decomposes a signal into a set of mutually orthogonal wavelet basis functions that are scaled and shifted versions of the time-localized mother wavelet [8]. When applying the wavelet transform, original image can be decomposed into four sub-band images. This wavelet decomposition can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower-resolution components [9]. The resultant sub-images obtained are LL, LH, HL and HH images which in turn are applied with different laws masks like ripple, wave, edge and spot. LL sub-image is applied with level mask, LH sub-image is applied with spot mask. Similarly wave mask for HL and ripple mask for HH sub-image. Laws texture energy measures determine texture properties by assessing average gray level, edges, spots, ripples and waves in texture. The measures are derived from three simple vectors. L3=(1,2,3) which represents averaging, E3=(-1,0,1) calculating first difference (edges) and S3=(-1,2 -1) corresponding to the second difference (spots). After convolution of these vectors with themselves and each other, five vectors result:

Level = [1, 4, 6, 4, 1]

Edge = [-1,-2, 0, 2, 1]

Spot = [-1, 0, 2, 0,-1]

Ripple = [1, -4, 6,-4, 1]

Wave = [-1, 2, 0,-2,-1]

Mutual multiplying of these vectors, considering the first term as a column vector and the second term as row vector, results in 5×5 Matrix known as Law's Masks. By convoluting the Law's Mask with the input steel SEM image and calculating energy statistics, a feature vector is derived that can be used for texture description and feature calculation. To extract texture information from an image $I_{(i,j)}$ of size (N×M), the image is convoluted with each two-dimensional mask [10]. Here E_5E_5 mask is used to filter the image $I_{i,j}$, the result was a texture image as follows:

$$TI_{E_5E_5} = I_{i,j} \otimes E_5E_5 \quad (1)$$

All the two dimensional mask except L_5L_5, had zero mean.According to laws, texture image $TI_{L_5L_5}$ was used to normalize the contrast of all the texture images (see equation 2). This step made these descriptors contrast-independent.

$$Normalize(TI_{mask}) = \frac{TI_{mask}}{TI_{L_5L_5}} \quad (2)$$

The output (TI) from Laws mask are passed to "Texture Energy Measurement"(TEM) filters (see equation 3).These consisted of moving non-linear window average of absolute values.

$$TEM_{i,j} = \sum_{u=-7}^{7}\sum[Normalize(TI_{i+u,,j+v})] \quad (3)$$

The different features like mean, standard deviation, kurtosis, entropy and skewness are calculated for the test images. They are:

$$Mean = \sum_{i=0}^{M}\sum_{j=0}^{N}(TI_{i,j}) \quad (4)$$

$$SD = \sqrt{\frac{\sum_{i=0}^{M}\sum_{j=0}^{N}(TR_{i,j} - mean)^2}{M \times N}} \quad (5)$$

$$Skewness = \frac{\sum_{i=0}^{M}\sum_{j=0}^{N}(TR_{i,j} - mean)^3}{M \times N \times SD^3} \quad (6)$$

$$Kurtosis = \frac{\sum_{i=0}^{M}\sum_{j=0}^{N}(TI_{i,j} - mean)^4}{M \times N \times SD^4} \quad (7)$$

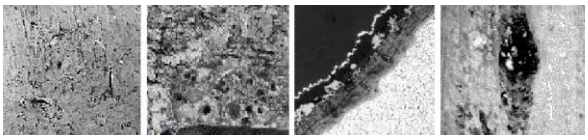
$$Entropy = \frac{\sum_{i=0}^{M}\sum_{j=0}^{N}(TI_{i,j})^2}{M \times N} \quad (8)$$

2.2 Testing using Laws masks

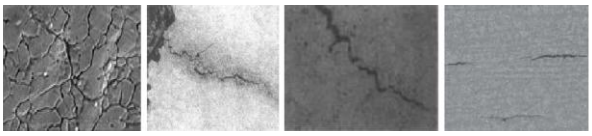
In testing phase, the input test image is applied with different laws masks like ripple, edge, wave, level and spot. Different feature values like mean, standard deviation, kurtosis, entropy and skewness are calculated for the output image. Finally accuracy assessment is done based on minimum distance calculated using the Sum of Squared Distance (SSD) value taken between the test and training set.

3. RESULTS AND DISCUSSIONS

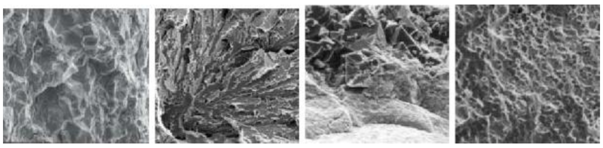
This section discusses about the results of the proposed method and its comparison with other methods like Tamura features, Gray Level Co-occurrence Matrices (GLCM) and Laws masks. Tamura and Mori explained the textural features corresponding to visual perception [11]. They proposed six texture features corresponding to human visual perception: coarseness, contrast, directionality, line-likeness, regularity and roughness [12]. For calculating these features, database for the test and training sets are used. Coarseness for corrosion, roughness for fracture and line-Likeness for crack and scratch defects are calculated. The GLCM based classification is a supervised form of classification. Haralick (1979) proposed the idea of statistical information of an image for its classification [13]. Features identified using this method are contrast, energy, entropy, mean, distance and standard deviation [14]. Another method for the comparison is applying laws masks to the input image directly and then calculating feature values for the masked images. This method obtained somewhat better results when compared to that of GLCM. The input images for corrosion, scratches, fracture and cracks in steel surfaces are taken into account in order to evaluate the performance of different types of feature extraction methods. Sample images of some defective steel parts are shown in figure 2.



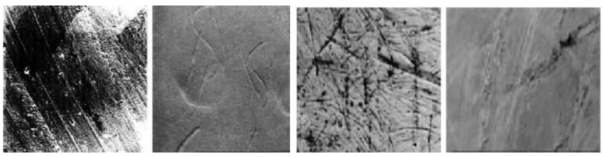
(a) Corrosion



(b) Crack



(d) Fracture



(d) Scratch

Figure 2. Sample SEM images of different types of defects in steel products

The minimum distance was calculated by taking the Sum of Squared Distance (SSD) between the feature values calculated for test and training images. Similarly the process is done for a set of 100 images in the database and the accuracy assessment is done.

TABLE 1. SSD obtained using Tamura features

Test / Training	Corro11	Fracture12	Scratch13	Crck14
Corro1	1.27	1.272	1.275	1.278
Fracture1	5.79	5.74	5.794	5.8
Scratch1	1.325	1.3	1.321	1.326
Crck1	2.62	2.623	2.648	2.76

The table 1 shows the sample classification of defects done by using tamura features method. This minimum distance calculation using SSD was carried out for the database containing 100 images with different type of defects. Here the highligted values indicate the correct classifications since they have a minimum value for same type of defect. The third and fourth row obtained misclassifications. The classification accuracy for this method is 64%.

TABLE 2. SSD obtained using GLCM method

Test / Training	Corro11	Fracture12	Scratch13	Crck14
Corro1	2.323	2.413	2.45	2.48
Fracture1	2.63	2.64	2.61	2.62
Scratch1	4.18	4.172	2.64	2.68
Crck1	3.03	3.0315	3.0313	3.134

The table 2 shows the results obtained using GLCM method. The different GLCM feature values obtained for test and training images in the database and SSD is calculated. It obtained equal almost equal number of correct and incorrect classifications. The classification accuracy for this method is 55%.

TABLE 3. SSD obtained using Laws masks method

Test / Training	Corro11	Fracture12	Scratch13	Crck14
Corro1	4.6	1.1	3.9	3.07
Fracture1	3.64	3.6	3.652	3.651
Scratch1	1.637	1.639	1.635	1.638
Crck1	4.04	4.057	4.058	4.045

The table 3 explains the sample classification of defects done by using Laws mask method. Here different Laws masks were applied to different defect images and laws features were calculated for both test and training images. The overall classification accuracy for this method is 73.5%.

TABLE 4. SSD obtained for the proposed method of DWT with Laws mask

Test / Training	Corro11	Fracture12	Scratch13	Crck14
Corro1	0.0159	0.4534	0.5155	0.1918
Fracture1	0.1860	0.0215	0.1980	0.027
Scratch1	0.6222	0.2727	0.0443	0.644
Crck1	0.4461	0.1194	0.474	0.1071

The table 4 shows the sample classification of the proposed method using DWT with laws masks. Test images were applied directly with different laws masks and laws features were calculated. Training images were applied with DWT and then sub-images were applied with laws masks and the feature values were tabulated. There was more number of correct classifications than misclassifications. The overall classification accuracy for proposed method is 82.5%. Same types of defects having the minimum distance are considered as correct matches and are highlighted in the tabular columns. These are sample classifications. Similar comparative results have been analyzed for all the images in the database.

3.1 Accuracy Assessment

From the results and discussions, it is inferred that the proposed method produce better results for defect classification. Accuracy assessment is done based on the minimum distance obtained from the comparison between the test and training sets. The bar chart shown below in fig.4 shows the overall accuracy of all the methods and a comparative study. The proposed method of DWT with laws masks have obtained the maximum accuracy when compared to other three methods. The comparative study for all the four methods is shown in Figure 3. It infers the number of correct matches obtained for each type of defect in all methods.

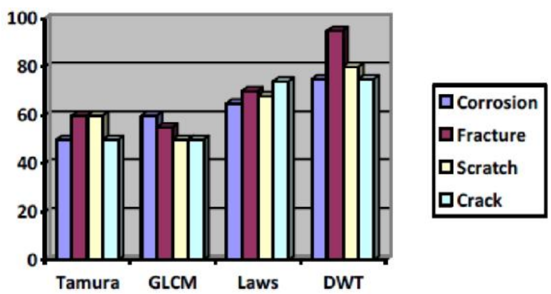


Fig.3 Bar chart showing comparative results

4. CONCLUSION

In order to realize the importance of automatic surface inspection system, DWT based laws masks method for texture feature extraction has been analyzed in this paper for the defect detection and classification in steel surfaces using imagery. The magnification of defects in SEM images provides an opportunity to analyze the steel surfaces at micro level variations. This approach involves texture feature extraction of the defects in steel surfaces using the Discrete Wavelet Transform (DWT) and application of different laws masks for the resultant sub-images and the accuracy is compared with classical methods. The results obtained, indicate that the proposed method have better classification accuracy when compared with other methods by obtaining an overall accuracy of 82.5%. Thus classification of defects is possible with image analysis and may be used for correlating service/failure conditions based on morphology of the products.

5. ACKNOWLEDGMENTS

Authors thank management and Department of ECE, Thiagarajar College of Engineering, Madurai for support and assistance to carry out this work.

6. REFERENCES

[1] Mike Muehlemann, “Standardizing Defect Detection for surface Inspection of Large Web Steel,” International Journal of Pattern Recognition and Artificial Intelligence, 2000, Pages: 735-755.

[2] Laurent karsenti, Rehovot, IL., “Method for defect detection and process monitoring based on SEM images,” 2010 US 7,764824 B2.

[3] R. Jeffery Price, W. Kathy Hylton, W. Kenneth Tobin, Jr., R. Philip Bingham, D. John Hunn and R. John Haines,

“Detection of cavitation pits on steel surfaces using SEM imagery,” 2008, (865) 574-5743.

[4] I.H. Son, J.D. Lee, S. Choi, D.L.Lee, Y.T Im, “Deformation behavior of the surface defects of low carbon steel in wire rod rolling”, Journal of materials processing technology,” 2008, 2 0 1pp. 91–96.

[5] Shigeru Takayaa and Kenzo Miyab, “Application of magnetic phenomena to analysis of stress corrosion cracking in welded part of stainless steel,”. Journal of Materials Processing Technology 2005, 161 66–74.

[6] Kuldeep Agarwal, Rajiv Shivpuri , Yijun Zhu, Tzyy-Shuh

Chang, Howard Huang, “Process knowledge based multi-class support vector classification (PK-MSVM) approach for surface defects in hot rolling,”. Expert Systems with Applications 2011, 38 ,7251–7262.

[7] S.G. Mallat, ”A theory for multiresolution signal decomposition: the wavelet representation,”. IEEE Trans. on pattern analysis and Machine Intelligence, 1989, 11(7): 674~693.

[8] W. Sun, M. Mujherjee, P. Stroeve, A. Palazoglu, J.A. Romagnoli, “A multi-resolution approach for line-edge roughness detection,” Microelectronic - 2773 -Eng. 86.2009, pp.340-351.

[9] Y. Han, P. Shi, ”An adaptive level-selecting wavelet transform for texture defect detection, Image and Vision Computing,” Vol. 25, No. 8,2007, pp. 1239-1248.

[10] M. Rachidi, A. Marchadier, C. Gadois, E. Lespessailles, C. Chappard, C. L. Benhamou, “Laws’ masks descriptors applied to bone texture analysis: an innovative and

discriminant tool in osteoporosis," DOI 10.1007/s00256-008-0463-2, 2008, 37:541–548.

[11] Tamura and Mori, H., Yamawaki. Textural Features Corresponding to Visual Perception. IEEE Transaction on Systems, Man, and Cybernetcs, Vol. SMC-8,No. 6, 1978, pp. 460–472.

[12] Hsin-Chih Lin, Chih-Yi Chiu, Shi-Nine Yang, "Finding textures by textual descriptions, visual examples, and relevance feedbacks," Pattern Recognition Letters 24, 2003, pp: 2255–2267.

Haralick, M. Statistical and structural approaches to texture. Proceedings of the IEEE 1978, 67(5): 786–804.

[13] Fritz Albregtsen, "Statistical Texture Measures Computed from Gray Level Coocurrence Matrices," Image Processing Laboratory Department of Informatics University of Oslo, November 5, 2008.