A new method to damages detection on steel surfaces

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Abstract: In any industry, quality control is an essential and inevitable part of process Quality control is an essential and inevitable part of industrial process. In any industry, quality control is an essential and inevitable part of process. Defect detection in steel plates, is one of the most important quality control steps in steel process. Image processing is a dominant technique to recognize defect in steel plates. in this paper a fast and highly accurate approach for detection of this kind of defects is offered by using image processing with the aid of 2D Gabor Wavelet and without any need to normal image or determining the quantity of images which are to be deleted. The accuracy and speed of applied approach has been indicated by offering test samples. The result show considerable improvement and Precision and speed of this suggested approach is compared to the previous methods. [Mostafa Sadeghi, Masoud Shafiee, Faezeh Memarzadeh Zavareh. **A new method to damages detection on steel surfaces**. *Life Sci J* 2013;10(2s):342-346] (ISSN:1097-8135). http://www.lifesciencesite.com**.** 59

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Introduction

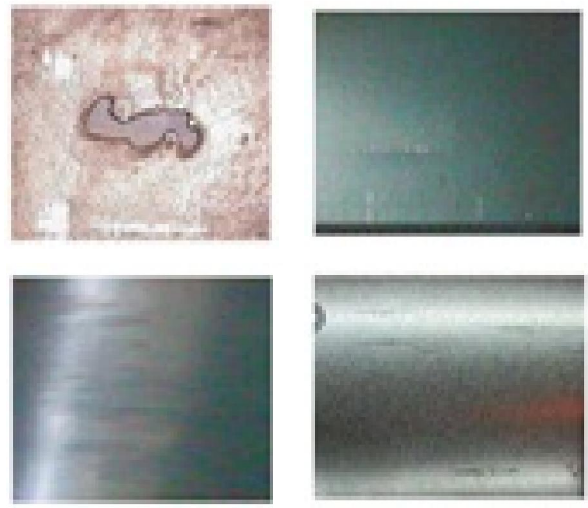
Quality control is an important issue in producing steel sheet. Detection of surface defect devotes a high percentage of quality control process to itself. Today, in most of sheet product lines, quality control is performed manually by expert people. The lack of an automatic quality control system causes reduction in efficiency, lack of sufficient precision, and increasing the expenditure. Image processing is the dominant technology in the field of inspecting different textures and recognizing available diversity. Capability of this technology, especially in this two contexts of detecting and categorizing the sample, opens the way to utilize this approach for quality control in industries such as textile, paper, ceramic. So far a great deal of research has been made in automatic detection of defects available on the surface of steel sheets [1,2]. Among other approaches used for locating the defects, we can name laplace filter, gradient filter, and RAF filter [3,4]. Application of these filters on images makes the defective edges and unimportant details of the screen to be exposed with the same intensity. By morphology methods application defect edges are eliminated. In reference [5] an approach for detecting steel defects is introduced. In this method at first local entropy is applied on the image pixels, and then morphology approaches are used to distinguish the defects from background.Total attempts which are so far accomplished, are mostly with the focus on the features of color, shape and texture, in order to introduce appropriate methods for defect detection. In approaches based upon texture analysis, the main purpose is to provide a criterion for detection of image texture properties, such as softness, flatness, coarseness, etc. some studies have also been performed based on Fractal Model[6] and co-occurrence matrix in defect detection of steel sheets.

Related Works

Due to capabilities of image processing in the field of assessment of different tissues and their classification, So far in most industries such as textile, Ceramic and paper, this technology has been used for QC and defect detection [1,2,3]. The concentration of last works has been on features such as color and shape. In [4, 5] the tissue feature is used, too. In detection of steel sheet defects, this technology has been used [13]. Among the most important methods for image processing are edge detection and utilizing smart sensors [6] and zoning the images [9]. In these methods with focus on color and shape features, the surface defect is detected. Due to imperfect information yielded from these methods (especially in shape feature) the type of defect is not recognizable. Unlike the color and shape feature, the tissue feature can give us the needed information to detect the defect and its type [10]. Some methods to combine the color and tissue features are presented [11, 12]. These methods have treat to tissue and color as a common phenomenon. In [13] a new method is presented to extract the steel surface features by using arithmetical method like LBP. In [4] by application of image processing technology with the aid of Gabor wavelet for extraction of tissue features and comparison with normal image, as well as manually determining the quantity of partial image to be deleted, a good solution is offered. The problem of this method is the selection of appropriate normal image (s) with the same background; regarding the fact that determining number of partial images for deletion is done manually.

Texture Analysis and Feature Extraction with Using Gabor Wavelet-Today

In various stage of steel sheet production, different effects are made on the sheet surface. In order to assure a good quality of products, producers should detect unexpected defect to prevent tem to occur continually, and make sure that their products meet the requirements of the users [7, 8]. In Mobarakeh Steel Complex of Isfahan, about 210 coded defects have been inspected from the viewpoint of similarity, lighting, features, imaging, and process algorithms. In this paper by considering such parameters as the frequency of defect occurrence, diversity in defect from, and importance of separation among them,4 type of defects, namely hole, scrape, lateral wrinkle, and corrosion are chosen for inspection (Figure1). The dominant technology for detection and classification of objects based upon apparent features, is the technology of image processing. Generally speaking, the operation of image processing is performed in 2 steps: feature extraction & classification. In the former, by determining the favored features, parameter selection, and method of extraction, these features are separated from the raw image to be optimized. In the latter, regions with similar texture are recognized and borders between different textures are determined. Of the most applicable methods used in the extraction of textural features, is the method of directional multi-frequency. In this approach Gabor Wavelet is extensively utilized. Gabor Wavelet extracts considerable textural features from image which includes both different directions and different frequencies [9,10]. This Wavelet due to begin optimal in both frequency and local domain, can utilize the benefits of signal processing in both domains [11-12]. If Gabor Wavelet is defined in local domain, it will be convoluted with the respected image and makes partial image. If it is defined in frequency domain, by taking a Fast Foureir Transform (FFT) from respected image, transfers it to frequency domain and then multiplies it by the Gabor Wavelet in that domain. By transferring the product to local domain, partial image is provided. Since the convolution in local domain is performed less quickly than multiplication in frequency domain, in this paper we use Gabor Wavelet in latter domain to extract the image feature faster.



Hole, Wrinkle, Corrosion, Scrape (From Top to Bottom)

Because most defect in steel surface are not made accidentally and production, a specific Gabor Wavelet may not be used for detection of any kind of defect. Therefore, in this paper we have Utilized Gabor Wavelet bank for feature extraction. Existence of various direction and frequencies in such a bank causes extract features to include lost of information about image texture, so that they can detect any defect in different frequency and direction very well.

The two-dimensional Gabor Wavelet Utilized in this paper is presented by (1).

$$G(u,v) = e^{-\pi\left[\frac{u_p^2}{\sigma_x^2}+\frac{v_p^2}{\sigma_y^2}\right]} . e^{-2\pi j(x_0 u + y_0 v)} \quad (1)$$

In (1), v_p and u_p are determined by using (2).

$$u_p = (u - w_x).\cos(\theta) + (v - w_y).\sin(\theta)$$
$$v_p = -(u - w_x).\sin(\theta) + (v - w_y).\cos(\theta)$$

(2)

I. In (2), W_x and W_y are central frequencies of the wavelet in directions X and Y. X_0 and Y_0 are horizontal and vertical displacement in local domain, respectively. In the experiments conducted, these values are placed: $X_0 = 0$, $Y_0 = 0$, $W_X = W_y$, $\sigma_X = \sigma_y$. Since no analytic approaches for optimization of Gabor Wavelet bank have yet been suggested, it is necessary to use a long trend of trial and error to find the best configuration for the Wavelet banks. After inspection of experiments conducted, it was concluded that by using a bank consisting of 12 Gabor Wavelet with frequencies $\left(\frac{\Omega_m}{2}, \frac{\Omega_m}{4}, \frac{\Omega_m}{8}\right)$ and angles $(0^\circ, 45^\circ, 90^\circ, 135^\circ)$, texture feature can be extracted well. Ω_m is the maximum image frequency and equals to half of image dimension m frequency domain. It should be noted that increase in the number of Wavelet above some extent, does not increase the efficiency much, but makes the calculation more complicated.. recommended approach

In this paper a method is suggested in which the defects are classified based on dispersal in partial images so that is no need to have normal image (s) or specify the number of deleted images. At first, feature extraction is performed by a bank of Gabor filters comprising 12 filters.

After yielding the 12 partial images, the energy of them is computed. The normalization process is performed according to relation (2):

$$f_{norm}(x, y) = \frac{f(x, y)}{\max(f)} \tag{2}$$

Where f(x, y) is the value of pixel in point (x, y) of partial image matrix. Max (f) are maximum value of pixels in partial image, respectively.

After this normalization, the value of pixel converts to a new value in [0, 1]. After this, the quantization is done. The goal of quantization is mapping the normalized value of each pixel to several values. We need n-1 threshold level to map each normalized value to n grey level. This process is according to (3):

$$\begin{aligned} &for\ k \in \{0,1,\ldots,n-1\} \\ &if\ \frac{\mathrm{k}}{\mathrm{n}} \le f(x, y) \le \frac{k+1}{\mathrm{n}} \quad \text{then} \quad f_q(x, y) = k \end{aligned} \tag{3}$$

Where f(x, y) is the grey normalized value of each pixel in normalized partial image and f_q is the quantized image with n grey level.

In this point, the partial images that more distinctly have defective region are selected for combination because this region or zone causes the features of these pixels to be more sensible than rest of the image which somehow includes non – defective region. In the image in which defect is not observed, usually the balance of calculated energy is approximately zero and dose not lie in the region of calculated dispersal. With algorithms offered, images are selected whose data dispersal is small. In a defective image, it is possible to select all partial images or no partial images. Thereby, in this method there is no need to know how many partial images must be eliminated. Also the need to select the normal image(s) for comparison is absolutely removed.

After the best partial images are selected, the combination step must perform to produce the feature plan. This work leads to detection of more defected regions and increasing the percent for correct detection of non-defective regions and percent for correct detection of defective regions percentage. For combination of images, we can use some addition methods. There are many methods to combine array information and in this paper we use the Bernoulli's combination rule. For three variables a, b and c, this method is defined as following:

$$comb(a, b, c) = a + b + c$$

Finally, after combining partial images, feature plan is made up. The computations in this method for dispersal criterion are based on variance. In these experiments after extraction of features by Gabor filter bank, making partial images and calculating the energy, variance of each partial image is calculated. Variance determines the square of differences between each vector and the average and divides it by the number of elements. The experiments were conducted in MATLAB. For calculation of variance in this software we used (4).

$$\sigma^2 = \frac{1}{n}\sum_{i=1}^{n}(xi - \bar{x})^2 \tag{4}$$

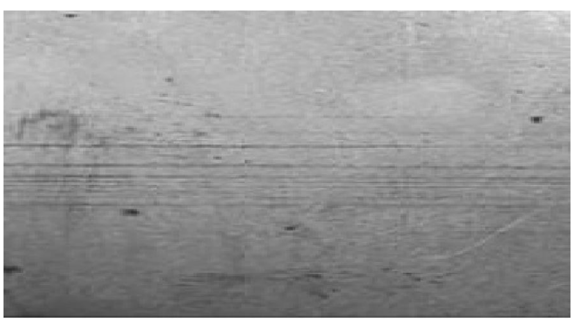
The resulted variance for all partial image is divided by its maximum value to be situated in similar area in the interval $[0\ \ 1]$.

This is performed because in some partial images, especially those with lower frequency, total value of pixels is less than the rest of partial images. If in this partial image there is an obvious defect, because the amount of its pixels is low, the achieved value for the variance will also be low, which does not have appropriate result. After normalizing the variance values, in order to select partial images for combination with each other, we need a threshold level. If variance is higher than a definite level of threshold, that partial image is chosen for combination. With respect to the images, this threshold level is considered as 0.2 by using the low of simple addition to combine partial images; a feature map is constituted which is a useful tool.

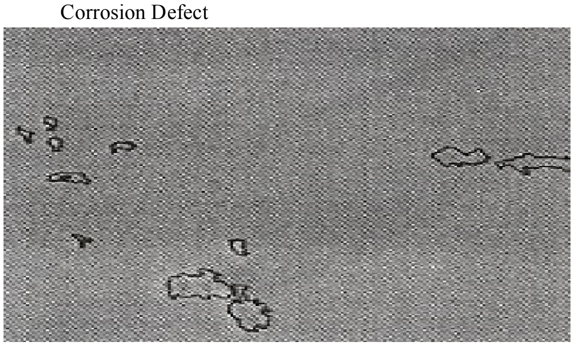
Set of Data and Experiments

To conduct such an experiment, we need various pictures which include different defects. The pictures used in this experiment consist of 100 real images 55 of which belongs to Kanpur university of India, and the other 45 are pictures taken from Mobarakeh Steel complex. In the experiments of this section, after feature extraction by Gabor Wavelet bank, construction of partial images, and calculation of energy, variance of each partial image is computed. The algorithm for selection of partial images with regions of defect is achieved based on variance value. Obviously, the image. situated in the limits of favored variance includes defect regions. In figure 2 an example of corrosion defect is shown. After performing the algorithm of defect detection, figure 3 is achieved. The results from executing this algorithm are indicated in Table 1.

In these experiments partial images are considered as non-normalized. Variances are normalized by dividing into their maximum value in the interval $[0 \quad 1]$. Threshold level is 0.2 and combination of partial images is performed by simple addition.



Corrosion Defect



Result of Applying the New Algorithm

RESULT OF APPLYING RECOMMENDED ALGOURITHM

Image Type	Percentage of Correct Detection	
	Correct detection of defective regions (%)	***Correct detection of no-defect regions (%)***
Real Image of Hole	95.42	96.89
Genereted Image of Hole	97.83	94.64
Real Image of Wrinkle	94.35	96.31
Genereted Image of Wrinkle	99.02	97.78
Real Image of Corrosion	93.32	95.93
Genereted Image of Corrosion	91.98	96.43
Real Image of Scrape	93.17	90.59
Genereted Image of Scrape	96.69	98.91

Conclusion

in this paper an approach is suggested to detect the location of defect on the surface of steel sheet by using Gabor Wavelet and variance. In this paper quantity of partial images was inspected in 3 modes: normalized, non – normalized and quantized with the threshold value of 5. Three variances were calculated for each mode and all partial images. The best elimination By normalizing the resulted variance of partial images, the values of variance changes and inappropriate partial images are selected for combination. All together, the amount of correct detection of defective regions in this approach has increased in comparison with other approaches. Values of partial images are inspected both normalized and non-normalized in the limit of [0, 1]. The best elimination By normalizing the resulted variance of partial images, the values of variance changes and inappropriate partial images are selected for combination. All together, the amount of correct detection of defective regions is improved in this approach with respect to other approaches.

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