Applying Wavelet in Image Processing For Visible Defect Detection on Steel Surfaces

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Abstract: Quality control of steel sheets for the purpose of optimizing product quality and maintaining market competition is very important. Detection of surface defects a high percent of quality control process to itself. 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.
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INTRODUCTION

Quality control is one of the most important issues in the industry of steed sheet production. Detection of surface defects allocates a high percent of quality control process to itself. Nowadays in most production lines of steel sheets, quality control is executed manually by expert personnel. The lack of an automated system for quality control causes a decrease in efficiency, increases costs and makes inaccuracy. Image Processing is dominant technology today for inspection of different tissues and recognition of available diversity. The power of this technology, especially in two fields of detection and classification of the template, makes it possible to utilize in quality control of such industries as textile, paper and ceramic. With regard to such practical background of techniques for image processing and the sort of surface defects available on the steel sheets, lots of researches has been made so far for the purpose of automatic detection of defects [1&2]. The majority of attempts so far made, focused on the features of color and figure in color to offer appropriate methods, In [3] the feature of tissue has been used, in which by utilizing Gabor wavelet for signal processing by MSMD method, tissue features of steel sheets are extracted. Since the availability of a normal image is vital for defect detection and proper selection of normal image is important (it must have the same background as that of defective image) and the comparison of normal image with defective ones is time –consuming and whit regard to the fact that detection of partial image which must be deleted is performed manually, in the new method the necessity to normal image is removed and the quantity of partial images to be deleted is determined automatically, so that the speed of defect detection is increased, whit accuracy maintained as before. To verify the ability of suggested method and compare it with the method mentioned in [4], a set of tests has been applied on real images. These tests verify increasing in speed while maintaining accuracy. In this paper, as well as introducing the advantages of utilizing automatic system for quality control, some of fundamental concepts required for this study are introduced concisely, in section 2. Similar attempts performed in the domain do utilizing image processing techniques for detection of steel defects are studied in section 3. Suggested model and results achieved is offered in section 4. In section 5 the results of the tests is indicated in two forms, namely table and figure. Finally in section 6 we conclude the paper.

BACKGROUND

In this section, first we survey defects, then introduce basic concepts in concise. During different phases of producing steel sheet, a lot of defects are provided on the sheet surfaces. producers of steel sheets are willing to recognize unexpected defects so that not to allow them to take place, frequently and make sure that quality of products coincides whit customer's need [5,6].In Mobarakeh steel complex about 210 defects are coded for appearance similarity, features of illuminance and imaging and processing algorithms and divided in 10 groups. Theses groups are surveyed in detail. Based on the outcome of this study and by considering such parameters as high frequency of defect occurring, diversity of defects and importance of their classification, 4 kinds of defect (hole, scrape, lateral pleat and corrosion) are chosen for study.

Image processing and techniques of feature extraction

Today dominant technology for detection and classification of products based upon appearance feature is the technology of image processing. Generally this operation is performed in two main phases, namely feature extraction and classification. In the former by determining the required features and by choosing parameters and method of extraction, the features are detected from a raw image and then optimized. In the latter phase, the regions with similar tissues are determined and the border of different tissues is detected. The main goal of feature extraction of tissues is to provide a criterion for detecting tissue properties of image, such as softness and roughness, cognation, flatness, frequency, being in order and so forth. There are different methods for extraction of tissue features; each one has its pros and cons with regard to its application, speed, accuracy, etc. Techniques like concurrent matrices or self – correlation function and approaches based on model are not applicable, because of complexity of calculation time for real – time inspection systems. Nevertheless, in most studies, these are used as methods with high accuracy. In this paper; the method of signal processing is utilized. The application is possible in two ways:

Filtering in time domain, analysis of Fourier domain and discrete transformations; Directional multi frequency method (MSMD). The most applied method used in extraction of tissue features and their classification is MSMD [7, 8,9].

Gabor Wavelet

Gabor filters are widely utilized in Directional multi frequency methods. These filters have high efficiency in feature extraction for tissue classification [10,11,12].Their main advantage is tissue analysis, simplification of directional band pass filtering in tissue image which allows the filter to extract a great deal of tissue features that includes both different directions and different frequencies. Gabor wavelets can be utilized in both frequency and locality domain. If Gabor wavelet is defined in locality domain, it convolves with under working image to produce the partial image. If Gabor wavelet is defined in frequency domain, first we apply the FFT on image to convert the locality domain to frequency domain and then multiply it with Gabor wavelet. Finally, by converting the response from frequency domain to locality domain, the partial image is produced. In this paper we use Gabor filter in locality domain.

Feature extraction is performed by a bank of Gabor filters. Because of different frequencies and different directions in Gabor filter's bank, the extracted features include high amount of information about the image tissue and so it is possible to detect the defects in different frequencies and directions. Since the major defects of steel surface occur in production period and in a random way, the special type of Gabor filter can not be applied in detection of any kind of defect.

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).

$$\begin{aligned} u_p &= (u-w_x).\cos(\theta) + (v-w_y).\sin(\theta) \\ v_p &= -(u-w_x).\sin(\theta) + (v-w_y).\cos(\theta) \end{aligned} \quad (2)$$

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.

SUGGESTED 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):

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

Where f(x, y) is the value of pixel in point (x, y) of partial image matrix. Min (f) and Max (f) are the minimum and 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):

$$for\ k \in \{0,1,...,n-1\}$$

$$if\ \frac{\mathrm{k}}{\mathrm{n}} \le f(x,y) \le \frac{k+1}{\mathrm{n}} \qquad \text{then} \qquad f_q(x,y) = k \quad (3)$$

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 be performed to produce the feature plan. This work leads to detection of more defected regions and increasing correct detection of non-defective regions and 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 SBA combination rule. For three variables a, b and c, this method is defined as following:

$$comb(a,b,c) = \frac{abc}{abc + (1-a)(1-b)(1-c)} \quad (5)$$

However we must note that the denominator of SBA formula in special cases can be zero and may lead to unacceptable results.

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).

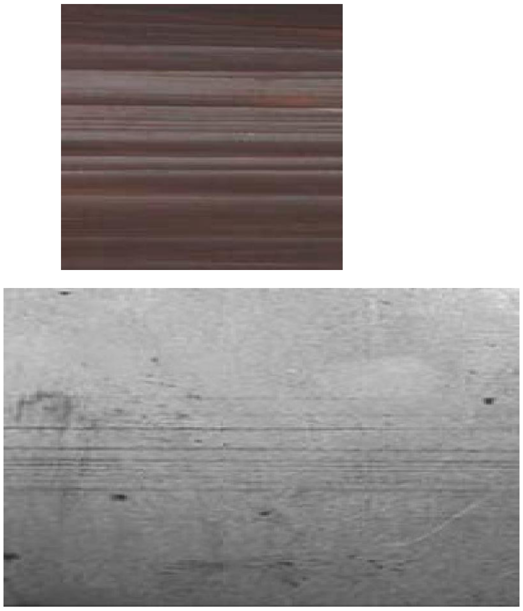
$$\sigma^2 = \frac{1}{n}\sum_{i=1}^{n}(x_1 - \bar{x})^2 \quad (4)$$

variance is divided into its maximum value in all partial images in each direction in order for all variances to be in the same limit and in the border of [0, 1]. The reason is that in some partial images, especially those with lower frequency, the amount of pixels is less than that of other partial images and if in this partial image there is a defect, because the quantity of its pixels is small, the resulted value for variances will be small too. This won't have a good outcome. After normalizing the values of variances for selection of partial images in order to be combined with each other and establish a feature plan, a threshold, that partial image is chosen for addition. This threshold is selected 0.2 with regard to images. Feature plan is established with combination of quantized partial images by means of simple addition rule. Now we create the binary image from the feature map. The binary image is produced by replacing the value "0" for the safe pixels and "1" for the defected pixels. Also, we can detect the edge of defect region using edge detection function and then by some morphology operation can bind the piece-wise and adjacent regions together to prepare an explicit image. Finally we should eliminate the alone pixels of defection, because they don't give useful information about the defection.

SET OF DATA AND EXTRACTION

By means of Gabor filter bank, establishing partial image is computed. The algorithm for selection of partial images having defective region is based on different values achieved for variance. Naturally, the image lying within the limit of our variance includes defective region. In Fig. 1, right hand shows the feature plans and left hand indicates related zoned selected images. The resulted feature plan is established by means of simple addition.

The average of results achieved from this algorithm is shown in table 1. In this table, SNS is the percent for correct detection of defective regions and SPC is the same percent for non-defective regions. The images on which experiments were conducted are divided two groups. Group 1 includes images on which the defects really exist. In group 2 there are images on which we made the defects manually. Results of both groups are offered. In showing the results, partial images are considered non-normalized and variances are normalized between 0and 1 by dividing them in to their maximum value. The threshold is considered 0.02 and the method used for combination of partial images is simple addition.



feature plan and zoned image

THE RESULTS OF SUGGESTED ALGOURITHM

Image Type	**Percentage of Correct Detection**	
	Correct detection of defective regions (%)	***Correct detection of no-defect regions (%)***
Real Image of Hole	98.23	94.20
Genereted Image of Hole	99.03	93.65
Real Image of Wrinkle	97.76	94.75
Genereted Image of Wrinkle	95.44	99.76
Real Image of Corrosion	95.12	97.93
Genereted Image of Corrosion	98.19	97.05
Real Image of Scrape	93.90	91.60
Genereted Image of Scrape	97.87	99.62

CONCLUSION

in the new approach by removing the need to normal image and automatic determining the number of partial images to be deleted, the speed of defect detection increases and mean while maintains the accuracy. 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 deletion algorithm was where variances of partial images were calculated in non – normalized mode. That is, normalizing and quantization causes the variances to be impressed and selection of proper partial images form them becomes impossible. All together, the amount of SNS in this approach has increased in comparison with other approaches.

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