Defect Detection in Alloy Steel Surface Using Nonsubsampled Contourlet Transform

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***Abstract*— Surface defect detection of metallic surfaces is a major challenge in any manufacturing industry. In this paper, an automated system to classify alloy steel surface based on Nonsubsampled Contourlet Transform (NSCT) is presented. Firstly the images are decomposed into different scales and directional subbands using Nonsubsampled Contourlet Transform (NSCT). The nonsubsampled contourlet transform is built upon nonsubsampled pyramids and nonsubsampled directional filter banks and provides a shift invariant directional multiresolution image representation. The image is decomposed at various scales and directions and the energy features are extracted. The energy features of defect and non defective surface are extracted and the best set that distinguishes the surface is used for classification.**

***Keywords*— NSCT, image classification, sub-band features, alloy steel surface.**

I. Introduction

Visual inspection of ceramic tiles industry using Wavelet Transform was proposed in [1]. The third level the coefficients of two dimensions Haar Discrete Wavelet Transform is used to process the images and feature extraction. At first the wavelet transform for an image free of defects which known as reference image is computed, and the image to be inspected which known as test image. Then the Euclidean distance similarity measure is used to decide whether the tested image is defected or not.

Automatic inspection of metallic surface defects using genetic algorithms is proposed in [2]. An experimental system has been developed to take images of external metallic surfaces and an intelligent approach based on morphology and genetic algorithms is proposed to detect structural defects on bumpy metallic surfaces. The approach employs genetic algorithms to automatically learn morphology processing parameters such as structuring elements and defect segmentation threshold.

A dissimilarity measure based on the optical flow technique for surface defect detection, and aims at light-emitting diode wafer die inspection is proposed in [3]. From an optical flow field, the dissimilarity measure of each pixel is derived. An automated visual inspection scheme for multi crystalline solar wafers using the mean shift technique is presented in [4]. Mean shift technique is used to detect the defects in a complicated background. This technique is then applied on an entropy image for removing the noises and to detect free grain edges. A simple adaptive threshold method is used to identify the defected surface.

To extract a set of features that can effectively address the problem of defect detection on hot rolled steel surface by using machine learning algorithm is explained in [5]. Two types of features are extracted with two and three resolution levels. They are wavelet and contourlet features. SVM classifier is used for detecting the surface into normal or abnormal. A unified approach for defect detection is proposed in [6] for finding anomalies in surface images. This approach consists of global estimation and local refinement. Global estimation is used to estimate the defects roughly by applying a spectral based approach. Then refine the estimated regions locally based on the pixel intensity distribution which is derived from the defect and defect free regions.

An effective deblurring method is proposed in [7] for surface defect detection on Gaussian blur images. Learned Partial Differential Equation (L-PDE) is applied for Gaussian blur images as a pre processing method. L-PDE model achieve much better results in comparison with the traditional image de-blurring methods. The detection of surface defects of the ceramic-glass based on digitized images is proposed in [8]. In order to gain the binary images threshold is used. Markov random field models are fitted to binary textures. This experiment is applied on the factory samples to verify the feasibility of this method.

A novel technique for detecting defects in fabric image based on the features extracted using a new multi resolution analysis tool called digital curvelet transform is proposed in [9]. The extracted features are direction features of curvelet coefficients and texture features based on GLCM of curvelet coefficients. K-nearest neighbor is used as a classifier for detecting the surface. A new method to detect the defect of texture images by using curvelet transform is presented in [10]. The curvelet transform can easily detect defects in texture, like one-dimensional discontinuities or in two dimensional signal or function of image. The extracted features are energy and standard deviation of division sub-bands.

Multi scale geometric analysis is employed in [11] to extract the statistical features of images in multiple scales and directions. Then, graph embedding algorithm is used to reduce the dimension of the extracted feature vector with higher dimension. In order to implement the proposed feature extraction method the grouping of curvelet transform and the kernel locality preserving projection algorithm is selected, and for testing the validity of the method the samples from hot rolling production are used.

The organization of the paper is as follows. The methodologies used in the proposed surface defect detection algorithm are introduced in Section 2. The proposed surface defect detection algorithm in alloy steel is presented in Section 3. The evaluation of the proposed system is presented in Section 4. Finally, the conclusion is made in Section 5.

II. Methodology

The proposed system for the classification of alloy steel surface into defected or non-defected is built based on NSCT. This section discusses some background information about contourlet transform related to the proposed system.

A. Contourlet Transform

Do and Vetterli proposed a “true” two-dimensional image representation scheme -- Contourlet Transform in 2002. It is a multidirectional and multiscale transform that can capture the intrinsic geometrical structure that is key in visual information. Unlike other approaches, such as Ridgelet and curvelet, that first develop a transform in the continuous domain and then discretize for sampled data, contourlet transform starts with a discrete-domain construction and then studies its convergence to an expansion in the continuous domain. Do and Vetterli [12] constructed a multidirectional and multiscale transform in the discrete domain by combining the Laplacian pyramid (LP) and the directional filter bank (DFB) using nonseparable filter banks, as shown in Figure 1, the same like wavelet. The Laplacian pyramid is first used to capture the point discontinuities, and then followed by a directional filter bank (DFB) to link point discontinuities into linear structures.

B. Nonsubsampled Contourlet Transform

Due to down samplers and up samplers present in both the LP and the DFB, the contourlet transform is not shift invariant, which will cause pseudo-Gibbs phenomena [13] around singularities. In 2006, L. da Cunha and J. Zhou improved the Contourlet Transform and developed the nonsubsampled contourlet transform [14]. Figure 2 displays an overview of the proposed NSCT. The NSCT is a fully shift-invariant, implementation. It is composed of two shift-invariant parts: 1) a nonsubsampled pyramid structure that ensures the multiscale property; and 2) a nonsubsampled DFB structure that gives directionality, without sampling as that in the Contourlet Transform. Because of its shift invariant property, we can achieve better results in the image processing tasks where redundancy is not a major issue, such as image de-noising and enhancement. Besides, it is more flexible for the design of the filter.

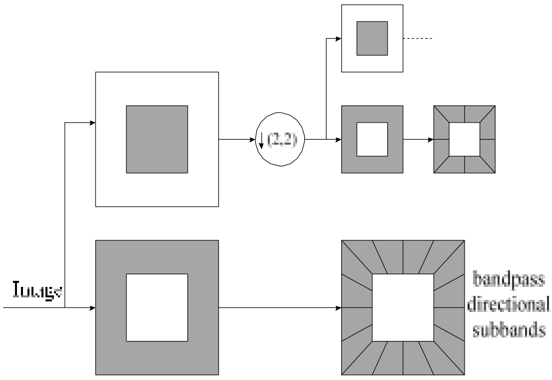

Figure 1. The flowchart of Contourlet transform

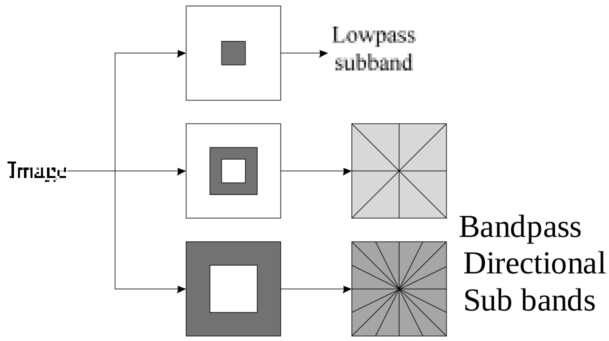

Figure 2. The flowchart of NSCT

III. Proposed Method

The NSCT is shift-invariant so that each pixel of the transform subbands corresponds to that of the original image in the same spatial location. The proposed approach is shown in Fig.3.

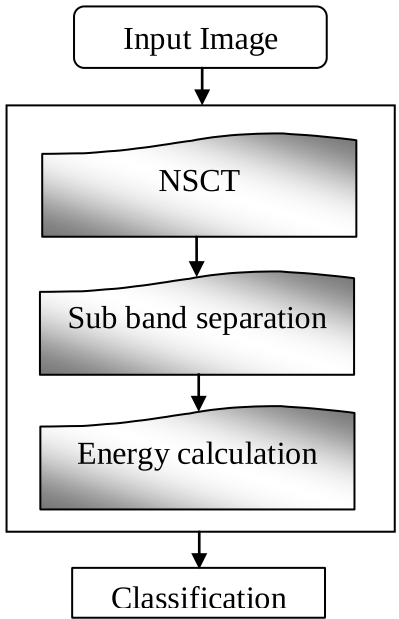

Figure 3 Automated system for the classification of steel alloy surface defect

In order to classify the given steel alloy image, the given image is decomposed by NSCT initially. It represents the given steel alloy surface into various frequency components at different decomposition level. In the NSCT the image is analyzed at various scales and directions. The image of 512x512 pixels when decomposed to any levels yields the image of 512x512 but with reduced resolution and detailed sub bands. The detailed sub-bands have the detailed information about the given image such as edges, textures. Due to this, only the detailed sub-bands are considered for classification analysis. The parameter used for classification is energy features computed from the detailed sub-bands. Among the various detailed sub-band energy, the best detailed sub-band is chosen for testing.

The steel alloy surface is characterized by the energy distribution of NSCT coefficients. The calculation of energy distribution can be done by taking the magnitude of coefficients. The energy of a sub-band is defined as the mean of the magnitude of the coefficients in that sub-band. It is given by:

$$Energy_e = \frac{1}{RC}\sum_{i=1}^{R}\sum_{j=1}^{C}\left|I_e(i,j)\right| \qquad (1)$$

where $I_e(i,j)$ is the pixel value of the eth sub-band and R, C is width and height of the sub-band respectively.

IV. Experimental Results

The performance of the proposed method is evaluated on 50 defect free alloy steel surface and 10 defected surface images. Fig.3 shows the images used for experiment. The top row images in the figure are no defect surfaces and bottom row images are defected images. The images are of 512x512 pixel.

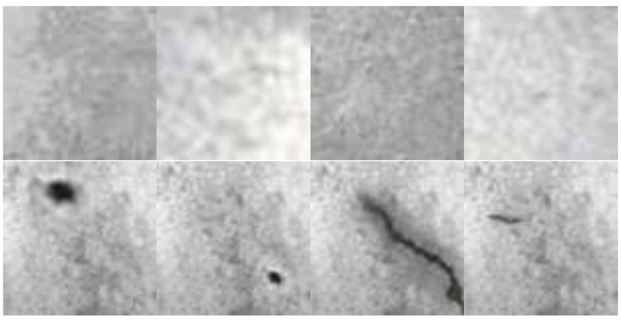

Fig 3. Training set images

TABLE I. Classification Rate of Contourlet Features for Alloy Steel Surfaces at 4^{TH} Level

S.No	Number of Directions	Classification rate (%)	
		Contourlet Transform	NSCT
1	2	75.96	77.81
2	4	78.64	80.62
3	8	82.14	82.5
4	16	83.26	84.37
5	32	83.58	87.81
6	64	83.98	89.37

The table displays the classification rate of the surface of various subbands of the test images at 4th level decomposition. As the size of the directional filter increases, the classification rate of the proposed system based on NSCT also increases. The performance of the proposed system is evaluated by varying the direction filter size used in the decomposition. From the table 1, it is found that NSCT performs better than Contourlet transform.

V. CONCLUSION

In this paper, NSCT based system for alloy steel surface classification is proposed. The classification of alloy steel surface into defect or defect free surface is done by using image processing techniques. The developed algorithm uses contourlet transform for feature extraction. From the result it is observed that over 89% classification rate is achieved by the system. However, the algorithm should be tested for surfaces having defects with various sizes and illumination variations, and this will be considered in the future work.

References

[1]. Elmougy, Samir, Ibrahim El-Henawy, and Ahmed El-Azab. "Model Based Ceramic tile inspection using Discrete Wavelet Transform and Euclidean Distance." arXiv preprint arXiv:1003.1811 (2010).

[2]. A Zheng, Hong, Ling Xue Kong, and Saeid Nahavandi. "Automatic inspection of metallic surface defects using genetic algorithms." Journal of materials processing technology, 2002: pp427-433.

[3]. Du-Ming Tsai,Yuan-Ze Univ., Taoyuan ,Taiwan,Yung Chiang and Ya Hui Tsai, "A

shift tolerant dissimilarity measure for surface defect detection", IEEE Transactions on Industrial Informatics,vol.8, no.1, 2012, pp 128 – 137.

[4]. Du-Ming Tsai ,Yuan-Ze Univ, Taoyuan and Taiwan Jie-Yu Luo, "Mean shift based defect detection in multicrystalline solar wafer surfaces", IEEE Transactions on Industrial Informatics, vol.7, no.1, 2011, pp 125 – 135.

[5]. Ghorai.S, Singh. R and Gangadaran. M, "Wavelet versus contourlet features for automatic defect detection on hot rolled steel sheet", Third International Conference on Emerging Applications of Information Technology (EAIT), 2012, pp 149 – 152.

[6]. Jiwon Choi and Changick Kim, "Unsupervised detection of surface defects: A two-step approach", 19th IEEE International Conference Image Processing (ICIP), 2012, pp 1037 – 1040.

[7]. Liang Wang, Yaping Hang,Siwei Luo, Xiaoyue Luo and Xinlan Jiang, "A new cluster based feature extraction method for surface defect detection: Deblurring Gaussian blur images: A preprocessing for rail head surface defect detection" , IEEE International Conference on Service Operations, Logistics, and Informatics, 2011, pp 451 – 456.

[8]. Jiaoyan Ai and Xuefeng Zhu, "Analysis and detection of ceramic glass surface defects based on computer vision, Proceedings of the 4th World Congress on Intelligent Control and Automation", vol.4, 2002, pp 3014-3018

[9]. Jianyun Ni, Jing Luo, Zaiping Chen and Enzeng Dong, "A multi resolution method for detecting defects in fabric images", Research Journal of Applied Sciences, Engineering and Technology vol.5,no.5, 2013, pp 1689-1694.

[10]. Moasheri, B. B. M., and S. Azadinia. "A new voting approach to texture defect detection based on multiresolutional decomposition." World Academy of Science, Engineering, and Technology 73 (2011): 657-661.

[11]. Xu, Ke, Yong-hao Ai, and Xiu-yong Wu. "Application of multi-scale feature extraction to surface defect classification of hot-rolled steels." International Journal of Minerals, Metallurgy, and Materials 20.1 (2013): 37-41.

[12]. M. N. Do and M. Vetterli, "The contourlet transform: an efficient directional multiresolution image representation, "*IEEE Trans. Image Process*, vol. 14, pp. 2091-2106, 2005.

[13]. R. R. Coifman and D. L. Donoho, *Translation invariant de-noising: Wavelets and statistics*. NewYork: Springer-Verlag, 1995.

[14]. A. L. Da Cunha, J. Zhou, and M. N. Do, "The Nonsubsampled Contourlet Transform: Theory, Design, and Applications," *IEEE Trans. Image Process*, vol. 15, pp.3089-3101, 2006.