A New Voting Approach to Texture Defect Detection Based on Multiresolutional Decomposition

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Abstract—Wavelets have provided the researchers with significant positive results, by entering the texture defect detection domain. The weak point of wavelets is that they are one-dimensional by nature so they are not efficient enough to describe and analyze two-dimensional functions. In this paper we present a new method to detect the defect of texture images by using curvelet transform. Simulation results of the proposed method on a set of standard texture images confirm its correctness. Comparing the obtained results indicates the ability of curvelet transform in describing discontinuity in two-dimensional functions compared to wavelet transform

Keywords— Curvelet, Defect detection, Wavelet.

I. INTRODUCTION

IN recent years, extensive efforts have been gone into automating human vision-based processes. Machine vision which is the result of these efforts plays an effective role in industry, especially in quality control of industrial products [1], [2], [3], [4], [5]. Among the subsets of the machine vision system, level visual inspection is the most important process in industrial quality control.

Quality control in industry has been designed and presented to ensure not giving defect products to customers. This process which has been doing by human for a long time, in recent years has been inclined to being mechanized [6], [10]. Visual inspection process of levels is recognizing areas which, according to defined standards, have deviated from intact samples [3].

At the present time, these methods are used in industry for detecting defects of many surfaces like cloth, ceramic tiles, wood, steel, silicon wafers, paper, leather, etc [3], [4], [7]. On the other hand, textures play a very important role in many applications of image processing and machine vision [8][9], and there are many applications in their analyzing and processing, one of which is defect detection.

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About three decades ago, texture analysis methods emerged [6], [10], [11]. In 1970's and the early 1980's, the presented methods in this field have been based on the first and second-order statistics of the gray level of image pixels like spatial domain grey level co-occurrence matrix (SDCM) and neighboring grey level dependence matrix (NGLDM). In the mid 1980's, model-based methods like Markov random fields (MRF) were presented as the other methods for texture processing.

Although they have a very long life, wavelets entered texture analysis domain in the late 1980's. Entering image processing methods like Gabor and wavelet transform, these methods replaced statistic methods [6], [10], [11], [12].

As we mentioned before, wavelets have some major weaknesses in analyzing two-dimensional signals like images; however, they have provided researches with significant positive results in texture analysis domain. Indeed, in texture analysis, especially in defect detection domain, the objective is to find discontinuities in texture images (two-dimensional function). Wavelets do not have enough efficiency in expressing two and multi-dimensional discontinuities. They can only describe zero-dimensional discontinuities (point) in one-dimensional functions, and since discontinuities in texture image are one-dimensional, wavelets will fail in detecting texture defects. In this paper, an appropriate mathematics tool called "curvelet" has been used to detect defect. Curvelets, unlike wavelets, can describe one-dimensional discontinuities well, even if they are curve and they can cover weakness of wavelets too. So far, this useful tool has not been used in detecting texture defect and it has been used more in problems of classifying textures. The remainder of this paper is organized as follows. In section 2 methods for texture defect detection are investigated. After introducing mathematics framework in section 3, the proposed method for texture defect detection is presented in section 4. Section 5 presents the simulation results. Finally, concluding remarks are given in section 6.

II. TEXTURE DEFECT DETECTION

In 1973 Haralick, Shanmugam, and Dinstein wrote "texture is very resistant to exact definition" [8]. But in Webster dictionary "texture" has been defined as "Surface feature characterized by arrangement, size, quality, etc." Other definitions of "texture" can be also found in articles on machine vision, for example, "a two-dimensional random

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discontinuous field with density function of common probability" or "repeated arrangements of a unit pattern on a surface".

But a logical solution to describe a texture can be extraction and definition of elements called "texture". Internal properties of those constructive elements like color and brightness can be called "tone". So, a set of elements with specified tones and structure describes a texture.

Two groups of texture analysis methods are statistic and image processing ones. Statistic methods of texture analysis investigate the gray level distribution in a texture. First-order statistics and pixel-based analysis can not model the texture. So, higher order statistics are used for texture analysis. The most common methods for texture analysis are co occurrence matrix, auto correlation function, and unit spectrum of texture [2].

Signal processing methods in texture analysis cover a wide area of spatial domain filtering. Signal processing methods which consider texture as a two-dimensional digital signal are very popular. Among these methods we can refer to Gabor and wavelet transforms methods.

In reference [7], adaptive wavelet has been used to detect defect in factory products. The object of adaptive wavelet is to maximize the ratio of wavelet transform energy between effective areas and intact area. Another method based on wavelet is presented in reference [13]. This method includes wavelet analysis, optimization of wavelet coefficients, and signal-to-noise ratio and is also able to implement on-line.

Neural networks by wavelet transform, in reference [14], have been used to detect texture defect. In this method, wavelet transform coefficients are applied to the perceptron neural network after feature extraction phase to train it. This is performed using quantization vector and main component analysis method. In [15], neural networks have been also used to detect defect in leather textures. Perceptron neural network uses five features including normalized density size, mean, variance, inertia, and entropy for making decision.

Wavelet transform along with co-occurrence matrices is also a useful tool which has been used to detect texture defect [6]. In this method, first wavelet transform is used to divide texture images into sub-bands. Then, using co-occurrence matrix, features are extracted from sub-bands; later, defective areas of texture are separated from intact areas using mahalanobis distance.

III. CURVELETS

In recent years, presence of curvelet transform in texture analysis domain has had a significant growth. But at the same time wavelet transform shows good efficiency in expressing one-dimensional functions and is not so much useful for two-dimensional signals like images. Wavelets' skill is describing zero-dimensional (point) discontinuities and they are not efficient for one-dimensional ones which occur in two dimensional functions like images. So, another analytic method with ability to express one-dimensional discontinuities is needed.

Ridgelets are useful tools to express one-dimensional discontinuities (straight lines), but their weakness is in describing curve-shaped discontinuities. Another analysis, therefore useful in describing this kind of discontinuities is needed.

A. The Curvelet Transform [16], [17], [18]

This transform was presented by Candes and Donoho in 1999 and covered weakness of Ridgelets. This transform has a directional prominent feature in wavelet scales and their elements support follows this relation:

$$(length \times length) \propto width \qquad (1)$$

Curvelets results from rotation, expansion, and delay of special functions as follows:

$$\psi_{a,b,\theta}(x) = a^{-3/4}\psi(D_a R_\theta(x-b)) \qquad (2)$$

Where D_a is the scale matrix and defined as follows:

$$D_a = \begin{pmatrix} 1/a & 0 \\ 0 & 1/\sqrt{a} \end{pmatrix} \qquad (3)$$

Where a is the scale parameter and lies in interval (0, 1). b is the location parameter and θ, direction parameter. R_θ is also a rotation with θ radian .

Curvelet transform includes the following steps:
- Dividing the object into a sequence of sub bands.
- Windowing each sub band into the blocks of appropriate size (depending on its central frequency).
- Applying the ridgelet transform to each block of the previous step.

Curvelet transform divides the spectral plane, as fig. 1 shows.
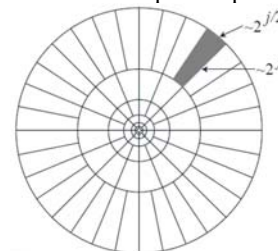

Fig. 1 Dividing the spectra plain by curvelet transform [17], [18]

Since in micro scales, curve discontinuities approach the straight line, ridgelet transform can be used to express them. So, curvelet transform is a useful tool to express curve-shaped discontinuities.

IV. THE PROPOSED METHOD

In this paper, a new method is presented to detect curvelet transform-based texture defect. The main idea is that defects in texture, like one-dimensional discontinuities are in two-dimensional signal or function of image. Since it expresses discontinuities of images, curvelet transform can easily detect defects.

Texture image I with dimensions m×m, where m is a power of two, first is divided into blocks with dimensions 16×16, then each block enters our proposed defect detection system (fig. 2).

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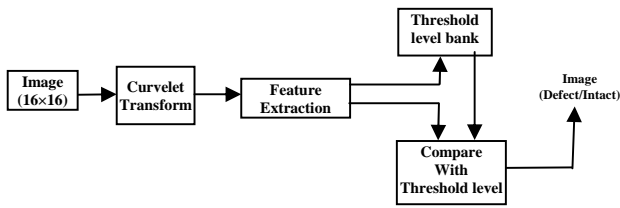Vol:5, No:1, 2011

Fig. 2 The proposed defect detection system

In the proposed system, a four-scale curvelet transform is taken from each block and in this process 26 sub bands are obtained as follows:

- The first scale including one sub band.
- The second scale including 8 sub bands (8 angles of 45˚)
- The third scale including 16 sub bands (16 angles of 22.5˚)
- The fourth scale including one sub band

In the second stratum of the proposed system, the re is a feature extraction block which selects prominent sub bands from 26 ones for decision making, using energy and standard deviation of curvelet transforms coefficients. Feature vector of each block is composed of two components of energy and standard deviation in the prominent sub bands, so that for each prominent sub band there are two components in the feature vector.

In the third stratum of the system, we can adjust the system to detect texture defect by selecting appropriate threshold level and comparing prominent sub bands with those levels. The selected threshold level based on energy mean difference and standard deviation of coefficients of the intact and defective texture samples is 3σ.

Parameters of feature extraction block (feature vector) and threshold level bank (threshold values) in the proposed system (fig. 2) are adjusted in training phase, and in testing phase these parameters are used to make decision.

We used the same system based on wavelet transform to evaluate efficiency of curvelet transform, but in the first stratum of each, one two-level wavelet transform is taken.

V. SIMULATION AND RESULTS

The proposed method was simulated on 20 textures from Brodatz album with size of 512×512 pixels. From each kind of texture, 4 different images were selected; one for training the system, one for adjusting it, and two for testing. We afflicted the second to fourth images of each texture with defect.

For the proposed system in fig. 2 which is based on curvelet transform, sub band 26 was selected as the prominent one. These sub bands in all studied textures differ considerably between intact and defective blocks. Graphs in fig. 3 and fig. 4 present energy and variance of curvelet transform coefficients respectively for all sub bands of defective and intact texture. The graph of intact texture is the average of 100

intact random blocks of the texture obtained in system training process. The graph of defective texture is average of 15 defective blocks of the same texture obtained in training process.

In the graph, increasing curves of 2σ and 3σ as well as decreasing ones of 2σ and 3σ of the average of 100 blocks have been presented. Sub bands higher than 3σ are known as prominent sub bands of the texture. In 20 textures and by intersecting the sets of prominent sub bands, only sub band 26 was selected as prominent one of energy and variance of all textures.
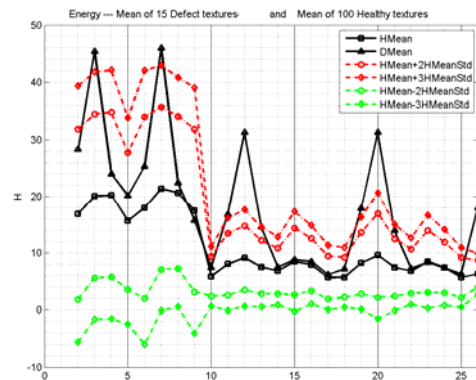

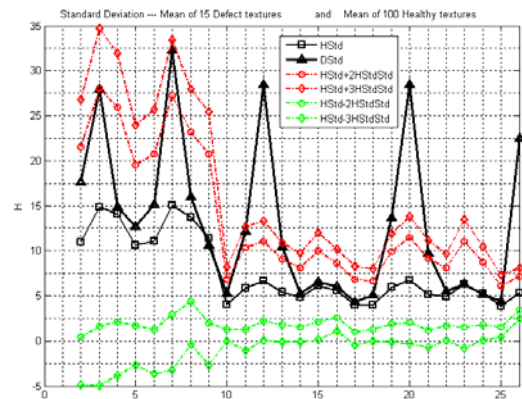Fig. 3 Energy of the curvelet Coefficients in all scales

Fig. 4 Standard deviation of the curvelet Coefficients in all scales

Adjusting threshold level is done in system adjustment phase, and in system testing phase the textures not entered and unfamiliar with the system are examined and tested. This same process was also performed for wavelet transform, but sub bands 5, 6, and 7 were selected from all 7 sub bands as prominent ones. Fig. 5 to fig. 7 show defective textures detected by the proposed system and based on wavelet and curvelet transform.

Table I expresses error (ER) and correctness (CR) percent of detection for two methods of wavelet and curvelet in the proposed system. Error percent is obtained from relation (4) and correctness percent of detection from relation (5).

$$Er = \frac{N_{cd} + N_{dc}}{N_{total}} \tag{4}$$

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$$CR = \frac{N_{cc} + N_{dd}}{N_{total}} \qquad (5)$$

In the relations above, defective blocks which are detected as defective have been shown by N_{dd} intact blocks detected as intact by N_{cc}, intact blocks detected as defective by N_{cd}, and defective blocks detected as intact by N_{dc}. Parameter N_{total} also equals 1024 which is the total number of blocks 16×16 in image 512×512.

Since presenting all the performed experiments is outside the scope of this article, only acceptable number of results as fig. 5 to fig. 7 and table 1 are presented. Results from applying the proposed method to the other studied textures have results near to the ones presented in this article. Fig. 5 to fig. 7 and table 1 show that the proposed method based on curvelet is better in detecting texture defect than the one based on wavelet.
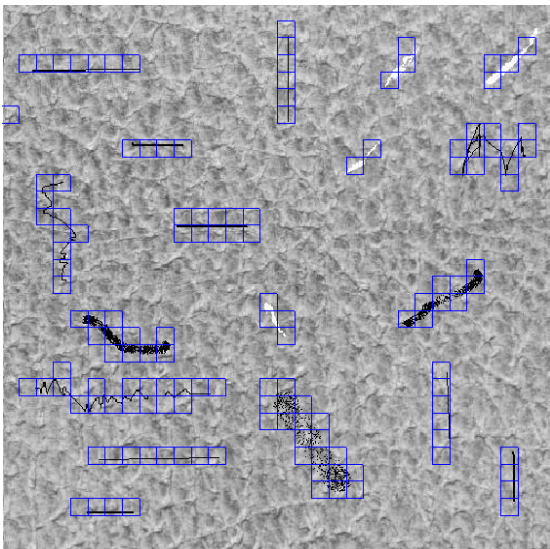

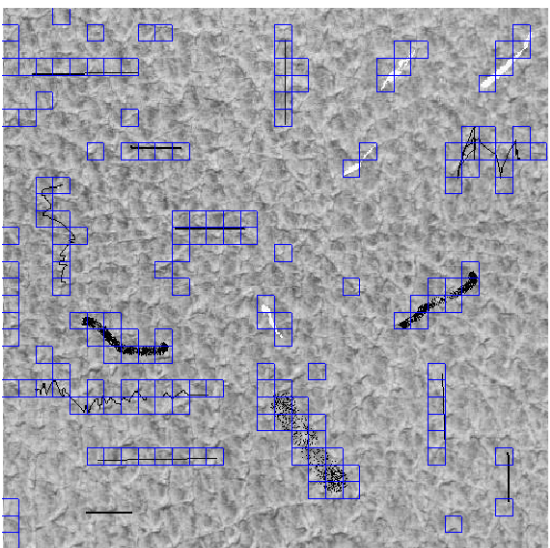Fig. 5(a) The analysis of the first texture with curvelet transform

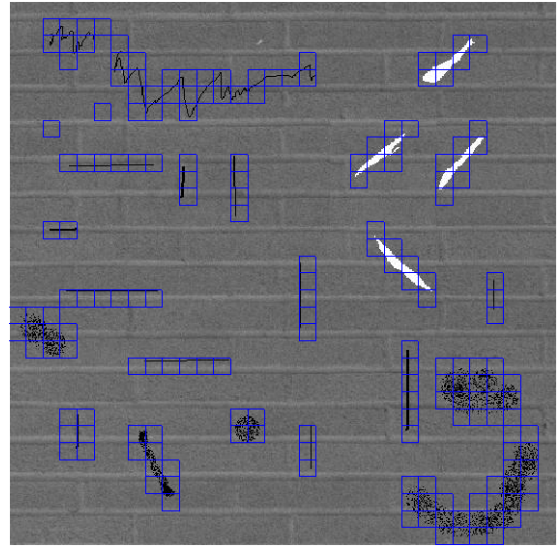Fig. 5(b) The analysis of the first texture with wavelet transform

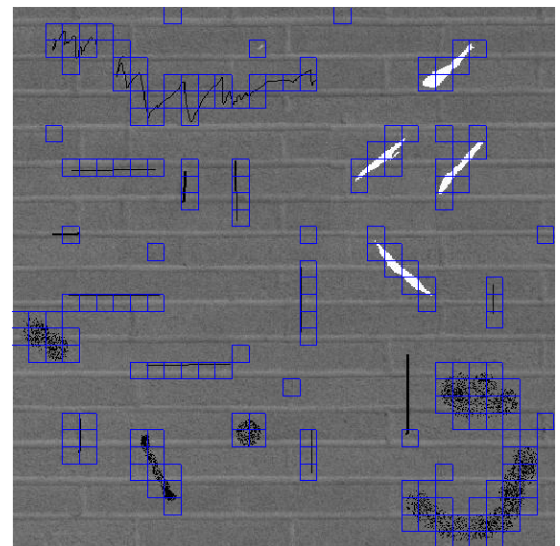Fig. 6(a) The analysis of the 2nd texture with curvelet transform

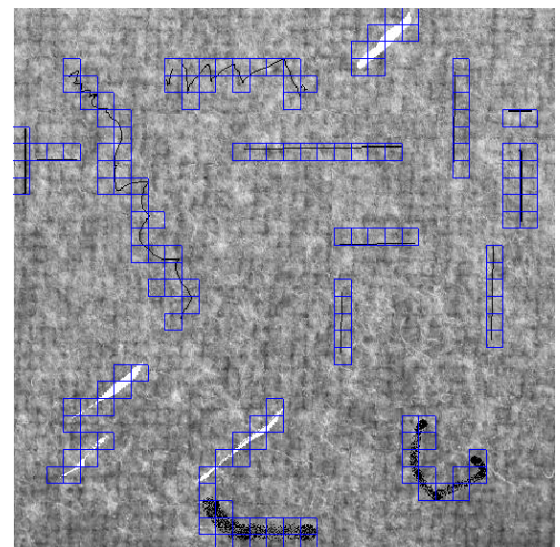Fig. 6(b) The analysis of the 2nd texture with wavelet transform

Fig. 7(a) The analysis of the 2nd texture with curvelet transform

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TABLE I
CORRECTNESS AND ERROR PERCENT AT THE 3 TEXTURES ANALYSIS WITH
WAVELETS AND CURVELETS.

		Curvelet		Wavelet	
Texture 1	N_{dd}	134	CR=98.7%	129	CR=95.5%
	N_{cd}	8		36	
	N_{dc}	5	ER=1.3%	10	ER=4.5%
	N_{cc}	877		849	
Texture 2	N_{dd}	179	CR=99.4%	172	CR=97.8%
	N_{cd}	5		17	
	N_{dc}	1	ER=0.6%	6	ER=2.2%
	N_{cc}	839		829	
Texture 3	N_{dd}	152	CR=99.4%	141	CR=97.9%
	N_{cd}	4		9	
	N_{dc}	2	ER=0.6%	13	ER=2.1%
	N_{cc}	866		861	

VI. CONCLUSION

In this paper, a system was presented to detect texture defects, using curvelet transform and extraction of energy features and standard deviation of division sub-bands. Since wavelets have problems in detecting discontinuities in images, It is expected that using curvelets cause detection precision to rise. Not only the results of the experiments revealed this subject, but the high rate of error detection in defective images confirmed the proposed system.

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