

Defect Detection of Tiles Based On High Frequency Distortion

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Article Info

Article history:

Received Apr 10, 2013

Revised Jun 2, 2013

Accepted Jul 8, 2013

Keyword:

Defect Detection of Tile
Defect detection,
Undecimated Wavelet Packets
neural network.

ABSTRACT

Quality control in Tiles Industry is of great importance. Therefore, it is effective to improve an automatic inspection system, instead of manpower, to increase accuracy and velocity and decrease costs. To this end, a new method to segment tile surfaces is offered in this study. This method aims at detecting defective areas in a tile, based on extracting features of edge defects. This method is based on the idea that human eye can better perceive the defects in a tile by looking at its edges. In the proposed method, first, in order to extract frequency characteristics resistant against transference, Undecimated Discrete Wavelet Packets transform is applied on images. Later, by computing local entropy values on high-frequency sub-bands images, those which appropriately include images defects are chosen to extract statistical features. Finally, Back propagation neural network method is used to determine segmented images containing defective areas. The obtained results, both visually and computationally indicate the higher efficacy of this method compared with the related state of the art methods.

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1. INTRODUCTION

With the increasing development of science and technology, using new discoveries in industry has been always considered by industry owners. Among the important industries, we can refer to tile and ceramic production plants which, by using technology, always try to improve their products quality. One important and substantial issue during production process is monitoring products quality. Currently, in most of great factories, the intended supervision and control are done by expert manpower that, compared to machines, is not only slower but also is characterized to become tired after working for several hours and to lose accuracy. From another point of view, we can refer to the difference between individuals' accuracy level. In other words, the defect which is explicit to an individual may be covert for another person. Therefore, using an automatic inspection system, instead of manpower, will be effective in increasing accuracy, velocity and reducing costs. Thus, such a system should be able to distinguish surface defects as accurately as possible. Since this involves many aspects and applications of machine vision, pattern recognition, and image processing, a variety of works have been done in this respect, which are not limited to tile and ceramic products. Among these works, we can refer to wood, cloth, steel, paper products and etc. For instance, Conner et al. [1] proposed a defect-detection method for wood. Defect detection was conducted through dividing the image in to smaller windows and classifying each window into one of defective categories such as, burl, corrosion, etc. They used combinations of features such as mean and variance plus texture features to improve classification. Iivarinen et al. [2], develop a defect-detection system to inspect surfaces which was

applicable in processing paper, plastic and wood industries. They applied co-occurrence matrix to feature extraction and used self-organized memories (SOM) for segmentation. Monadjemi et al. [3] offered a method based on the utilization of specific filters in order to classify with tile textures. Among the other works conducted in the field of tile surface segmentation, we can refer to [4, 5], in which segmentation is conducted by applying texemidea. Texemidea implies that each image can be created through matching different-size parts of overlapping images.

In recent decades, worthwhile multiplying techniques such as Gabor and wavelet transforms were widely used in issues of texture analysis. Based on human vision system, Gabor filters decomposed input images to small images in different directions and frequencies using filters. Different directions and frequencies in a filter bank cause the extracted features to contain a great amount of information on image texture. Two of the main shortcomings in Gabor filters are their large amount of computation and non-orthogonality, leading to a considerable lack of correlation in the intended bank filter output. Wavelet analysis is considered as one of the appropriate solutions to solve this problem, which is widely applied in texture analysis issues. Different methods, based on wavelet transform, have been proposed for surface defect detection. For instance, Amet et al. [6], proposed wavelet transform method and texture features extraction using co-occurrence matrix on the images obtained from wavelet transform to classify fabric defects. Rimac [7], specified tile defects through using wavelet transform and radial basis probabilistic neural networks. Ghazvini et al. [8], offered the method of applying wavelet transform and extracting statistical features from sub-bands and perceptron neural network for classifying defective tiles. In spite of many advantages of discrete wavelet transform a major problem exists is the lack of shift invariance [9]. Many studies have been conducted in the given field and on the utilization of Undecimated Discrete Wavelet Transform in order to extract features resistant against transference, among which we can mention to [10, 11].

In the present study, in order to use features of all sub-bands in different directions and frequencies and obtain useful information on defect detection as well as solve aforementioned problem, a new algorithm is offered. The proposed system to segment tile surfaces is formed to extract features through using suitable high frequency sub-bands of Undecimated Wavelet Packet Transform algorithm and also obtain useful texture features from co-occurrence matrix and variance. Finally, back-propagation neural networks method is used for classification.

This article includes five sections: Following the introduction, in the second section feature extraction through Undecimated Discrete Wavelet Packet Transform, and in the third section, the way of obtaining texture feature by co-occurrence matrix are explained and In the next one, the proposed algorithm for segmenting the defects is presented. The final section includes discussion and conclusion of the study.

2. FEATURE EXTRACTION THROUGH UNDECIMATED DISCRETE WAVELET PACKETS TRANSFORMS (UDWPT)

Standard Discrete Wavelet Transform is not suitable for defect detection as it is not shift- invariant. A defect in different displacement of tile image may result in different wavelet coefficient so lead to different detection result. So UDWPT is used in this paper. The most important advantages of UDWPT is shift-invariant which is suitable for defect detection [12]. UDWPT is similar to DWT, but has a difference in the reduction of output being impossible. This definition is defined as two different but equivalent algorithms called Mallat [13] and Troun [14].

In this paper, Troun algorithm has been used because of its simplicity compared to Mallet. Troun algorithm operates similarly to DWT. The only difference is that the UDWPT does not down-sample the wavelet coefficient, instead it up-samples low-pass and high-pass filter by inserting zeros. Figure.1 demonstrates the process of UDWPT.

3. GRAY LEVEL CO-OCCURRENCE MATRICES (GLCM)

Standard Discrete Wavelet Transform is not suitable for defect detection as it is not shift- invariant. A defect in different displacement of tile image may result in different wavelet coefficient so lead to different detection result. The Gray Level Co-occurrence Matrix is considered as one of the first texture feature extraction methods, showing second-order statistical properties of an image. This method was introduced in 70s by Haralick [15].

For image X consisting of N gray level, the Gray Level Co-occurrence Matrix, is defined as an $N \times N$ matrix which is defined for specific distance d and direction θ , showing in equation 1 [16].

$$\phi_{d,\theta}(i, j) = \sum_{u=1}^u \sum_{v=1}^v p(x(u, v), x(u', v'), i, j) \tag{1}$$

Where, U×V is image size, d and θ are, respectively, distance and direction between pixels pairs, and p is defined as follows:

$$p(x(u, v), x(u', v'), i, j) = \begin{cases} 1 & \text{if } x(u, v) = i, x(u', v') = j \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

In fact, each element of $\phi_{d,\theta}(i, j)$, indicates the number of gray-pairs occurrences (i, j) between pixels in the distance of d and direction of θ.

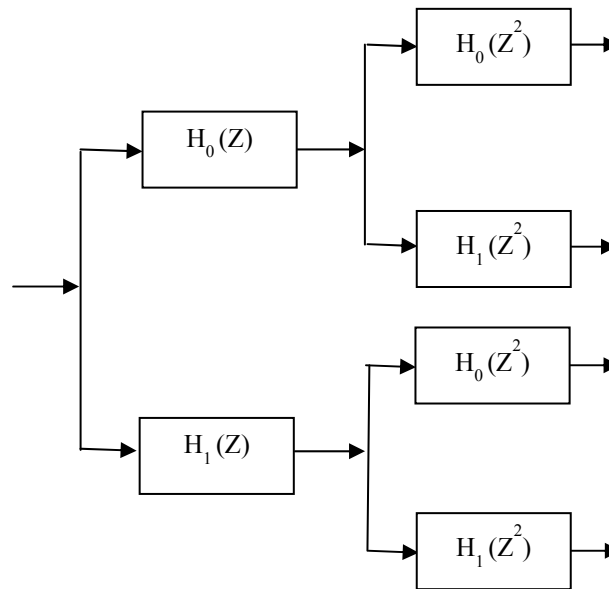


Figure 1. Wavelet Transforms of an image in two scales

The Gray Level Co-occurrence Matrix can present specific features of a texture image. For instance, if huge volumes are gathered around diagonals of matrix, then the texture image will be a rather large image. However, it must be mentioned that the Gray Level Co-occurrence Matrix cannot apparently indicate texture features in all cases. Therefore, having finished the calculation of co-occurrence matrices, the next step is to extract texture features obtained through appropriate function of ϕ . Haralick [15], has presented 14 functions in this field, among which 5 frequently-used functions are offered [17]:

Entropy is a criterion for the evaluation of image complexity. In other words, complex textures have high entropy.

$$ENT = \sum_i \sum_j p(i, j) \log p(i, j) \tag{3}$$

A contrast feature is a criterion for image contrast or local intensity variation in images.

$$CON = \sum_i \sum_j (i - j)^2 p(i, j) \tag{4}$$

Angular second momentum is a criterion for uniformity of image. For images with constant textures, it is equal to one.

$$ASM = \sum_i \sum_j \{ p(i, j) \}^2 \quad (5)$$

Inverse difference momentum is a criterion of homogeneous in images. Homogeneity is the most useful feature of detection of abnormal textures.

$$IDM = \sum_i \sum_j \frac{1}{1 + (i - j)^2} p(i, j) \quad (6)$$

4. PROPOSED ALGORITHM FOR DEFECT DETECTION

In figure 2, the whole steps of the proposed algorithm are shown. As the figure indicates, first, in order to extract frequency features, Undecimated Discrete Wavelet Transform is used. The purpose of using it is to use characteristics of edge defects, which are only detected by means of high-frequency filters. When sub-bands are formed, the entropy value of each high-frequency image is determined in defect area and those sub-bands with entropy less than a given threshold are chosen. Then, high-frequency coefficient of the chosen sub-bands are shifted between 0 and n and quantized in to $n+1$ integers. Later, vector of useful texture feature is formed by applying co-occurrence matrix (as for section 3) on the chosen sub-bands. In the following steps, in order to use the whole sub-bands information, the variance feature of all sub-bands and adding to texture feature vector are used. Thus, final feature vector is obtained. After extracting feature vector, a classification on feature space is applied to discriminate between non-defective and defective windows. There are different techniques in this respect, among which, back-propagation neural networks method is applied in this study.

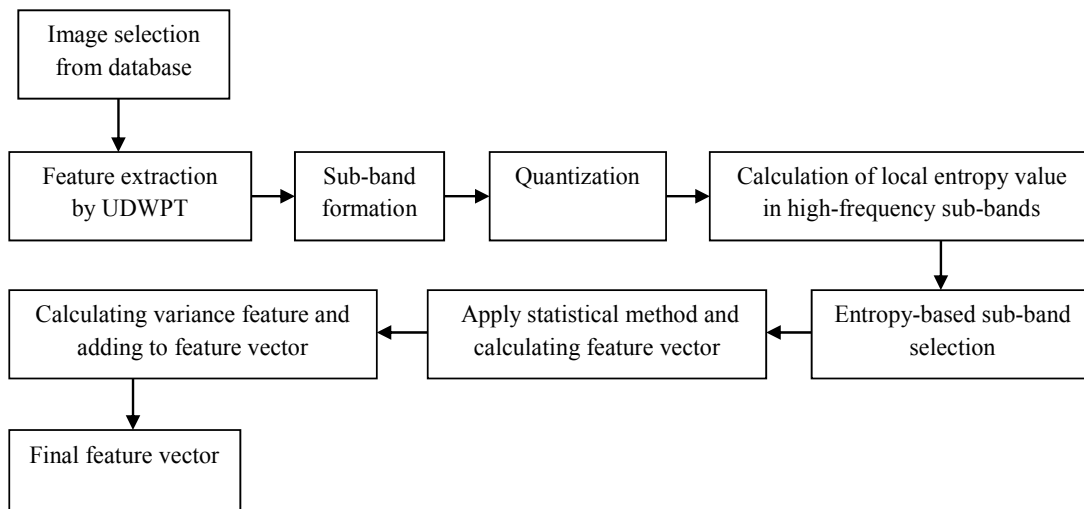


Figure 2. Total steps of the proposed algorithm to form feature vector

a. Edge and its Beneficial use for Texture Defects Detection

Edge detection, is one of the important concepts in image processing. The purpose of edge detection is to mark areas of an image in which illumination intensity varies quickly. In other words, edge is the border between areas with different properties in gray level surfaces. According to definitions stated about edge, focusing on defective texture images helps us to realize that human eye can better perceive the defects in a tile by looking at its edges. In fact, the majority of probable defects on tile surfaces images are considered as defects due to the illumination jumps they cause. As for what mentioned here, we are looking for using characteristics of edge defects in images to increase system defect-detection accuracy

b. Entropy Value Calculation and Sub-Bands Selection

Detecting image details amount greatly influences on edge detection efficacy. Thus, using criteria that can slightly describe these image characteristics can be more useful. Of the given tool types is local

entropy which, indeed, offers information on edge distribution [18]. To calculate the entropy value in a window, p_i is supposed to be probability of level i in the local window. Then, the local entropy H is defined as follows:

$$H = -\sum_i p_i \log p_i \quad (7)$$

The important point to be considered when using this concept is that for windows consisting of edge pixels, the local entropy will be of little value. Also if there are no edges, high-frequency factors will grow more randomness properties resulting in increasing the entropy value. The randomness property of high-frequency factors is the reason of the tile designs or of the noise applied while imaging. In case of having edge defects, random nature of factors will slightly decrease and subsequently, the factors entropy will be lowered. To apply the given point, the local entropy values of the intended window are calculated through selecting a window around the defect area in each high-frequency sub-band. Then, the local entropy values in several neighbors of defect areas are calculated, and each single neighbor's distance from the defect area's entropy is computed. The average obtained from these distances is considered as a criterion to evaluate the intended sub-band efficacy in detecting defect which is called sub-band efficacy factor. Finally, by selecting an appropriate threshold level obtained experimentally, we can decide that those sub-bands having both an efficacy factor and an energy level higher than the intended threshold are considered as sub-bands that can be utilized to apply co-occurrence matrix.

c. Variance Feature Calculation

Undecimated Discrete Wavelet Packets Transform decompose the main image into sub-bands in variant directions and scales. Each sub-band image contains variant information on image and defects on it. Therefore, it is essential to use all sub-bands information to obtain the sufficient accuracy for distinguishing defective area from intact one. Histogram of wavelet transform factors in detail sub-bands is similar to Gaussian functions, and since these functions are specified through dispersion criteria such as variance [19], we apply the statistical property of variance. To form feature vector using variance, first, each detailed image of sub-bands is divided into non-overlapping windows. Then, in each window, the variance value is calculated and added to the feature vector, which is obtained from feature vector of co-occurrence matrix. Doing so, the final feature vector is formed.

d. Error Back-Propagation Algorithm

This algorithm is a reduced recursive gradient algorithm used to train feed-forward multi-layer neural networks which are generally called multi-layer perceptron (MLP). The error back-propagation algorithm process is composed of 2 main paths: forward path and backward path. In the forward path, a training pattern is applied to the network and its effects are propagated through central layer to external layer. Finally, in the real external path of network, a number of layers are obtained. It must be mentioned that in this path, parameters like weight matrix and bias vectors remain constant. In the backward path, contrary to the forward path, network parameters are changed and arranged based on error correction code. In other words, we are looking for bias vectors and weight vectors to minimize the error as much as possible. This algorithm, first, starts from an arbitrary value for weights and then, in each phase, changes the weights to reach the possible minimum error.

5. EXPERIMENTAL RESULTS

Image collection includes 411 images from 6 types of tiles with variant patterns. Of these, 80% are defective and 20% are intact images. In figure 4, the intact samples of the given 6 types are shown. In order to run experiments and justify the proposed algorithm, some parameters are arranged. As for feature extraction, first, bio-orthogonal filter factors were applied to decompose images into sub-bands by using UDWPT method. The given filter factor includes 2 types of BS 2/2 and BS 3/9. These numbers are indicatives of degree of polynomial and filter length respectively. In this study, BS 2/2 is used. After extracting frequency features, it is realized that sub-bands quantization is equal to 256 (8 levels). The experiments have been conducted for values of 3, 5 and 6, in which the results were related to 8 bits and thus, this value was taken into account to run the experiments. Then, before applying co-occurrence matrix, selected sub-bands images were divided into non-overlapping windows. These windows' size is examined according to their textures' characteristics. The windows' size is arranged in according to the basic method [11] by which the best result is obtained using windows of size of 8×8. In the presented work, there exists no

decreasing sampling and image dimensions are not halved, hence windows of size 16×16 are used. In classification, 70% of samples were chosen for training and 30% were selected for network testing.

Table **Error! Reference source not found.** The results obtained from the proposed method

P	SPC	SNS	DATA SET
71/92	82/99	60/85	A
33/97	71/99	96/94	B
16/88	52/99	82/76	C
30/86	56/98	05/74	D
75/94	42/99	08/90	E
58/91	70/99	46/83	F
80/91	45/99	16/84	Ave

To assess the classifiers in this article, 3 criteria were applied: 1) SNS criterion, the presentation percentage of well-distinguished defective pixels, 2) SPC criterion, the presentation percentage of well-distinguished intact pixels, and 3) P, the total accuracy obtained from the 2 criteria average. As shown in table 1, the accuracy obtained from the proposed algorithm is, at its best, 97.33 and of group B, and at its worst, 86.30 and of group D. The obtained results, compared to the results of method used in [11] shown in table 2, indicates accuracy increase. Likewise, Figure 3 illustrates the performance of our method in term of total accuracy in comparison with the basic method. Figure 4 also shows the results of segmenting surface defects obtained from each 3 methods.

Table **Error! Reference source not found.** The results obtained from basic method [11]

P	SPC	SNS	DATA SET
86/76	98/99	74/54	A
91/43	99/45	83/42	B
82/51	98/60	66/43	C
81/53	97/66	65/40	D
90/29	99/30	81/28	E
86/43	99/47	73/40	F
86/49	98/91	74/07	Ave

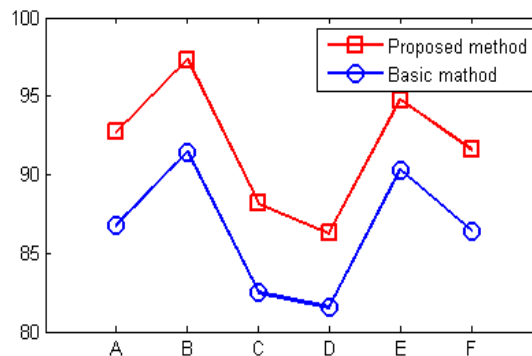


Figure 3. Total error comparison chart between proposed method and the basic method

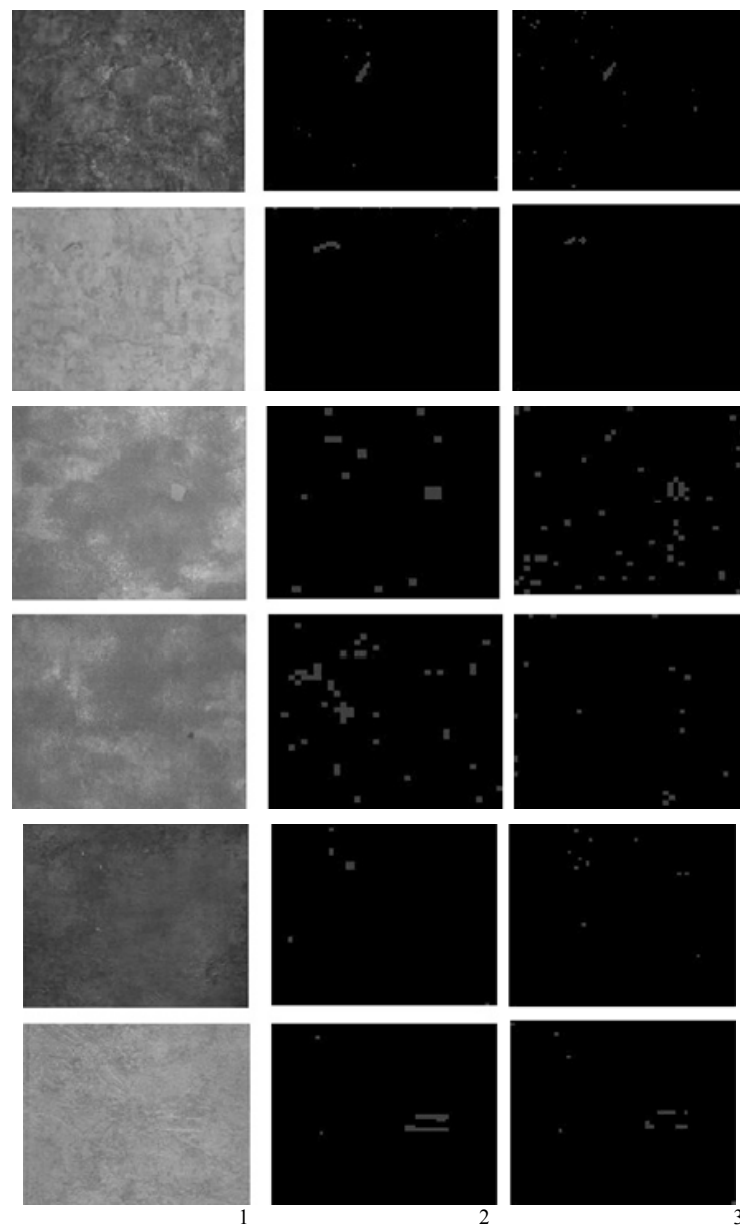


Figure 4. The visual results obtained from the methods 1) Images tile defect detection 2) defect segmentation with proposed method 3) defect segmentation with basic method [11]

6. CONCLUSION

In this research, a new method is proposed to detect defective areas in a tile based on feature extraction of edge defects. The given work is established on the idea that human eye can better perceive the defects in a tile through noticing its edges. The proposed method is based on applying co-occurrence matrix for high-frequency sub-bands of Undecimated Discrete Wavelet Transform. The results obtained from examining data collection of tiles images, contain SNS, SPC parameters and their averages. The simulation results indicate the superiority of the proposed method to the state of the art method in detecting tile defects. The more efficacy of the proposed method is because of its high utilization of edge defects characteristics in tile images.

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