Defect Detection of Tiles with Combined Undecimated Wavelet Transform and GLCM Features

Afsane Fathi, Amir Hassan Monadjemi, Fariborz Mahmoudi

Abstract— Development of an automatic defect detection system has a major impact on the overall performance of ceramic tile production industry. With this in mind, in this paper, a new algorithm has been offered for segmentation of defects in random texture tiles. firstly, by using undecimated discrete wavelet Transform (UDWT), frequency features of textures which are robust towards transition could be extracted. Then a co-occurrence matrices of sub-bands, in order to extract texture information, is obtained. Finally, after obtaining special characteristics from the combination of the two new methods, a back propagation neural network is applied for segmentation which is the final product of this. The results, both visually and computationally, show a higher accuracy while using this method than the conventional wavelet method and co-occurrence matrices that was utilized previously. The reason could be its independent from scale and rotation nature compared to the typical transform. Different locations of defects make different wavelet coefficients and ultimately increase the defect segmentation performance of a wide variety of defects.

Index Terms— Defect detection, Wavelet Transform, Undecimated Wavelet Transform, Co-occurrence Matrices, Back-Propagation Neural Network.

I. INTRODUCTION

Advances in science and technology allow to massive practical use of new achievements for any kind of industries. Amongst major industries, ceramic tile factories have intended to use new technologies to improve quality of their products. One of the important critical cases in the production is quality control of final products.

This kind of control allows specialized grouping of products, allows for more efficient policies for each category and decrease the cost. Also, this kind of supervision allows for some defects to be recognized and resolved before furnace processing. Losses in production will therefore be vastly reduced. Use of an automatic inspection system should also be able to detect defects on the surface with higher accuracy.

Since this involves many aspects and applications of machine vision, pattern recognition, and image processing, it has recently taken a large amount of research to deal with. instead of human recourses has a great influence on precision, velocity, and is cost efficiency. Such a system should also be able to detect defects on the surface with higher accuracy.

For instance, Monadjemi et al. [1] proposed a new method based on the use of special filters in order to classify random texture tiles. Xie et al. [2] represented a new method based on texture construction components which was called "Texem", to segment the defects. They firstly assumed that each image is generated by a superposition of various-sized image patches. Then, based on the distance method, which is learnt using a few normal images and also the likelihood criteria, would detect defects for random texture tiles. Novak [3] tried to detect defects on random texture tiles using statistical features. The author extracts a texture feature vector using a local binary pattern operator for defect detection.

In recent decades, worthwhile multiplying techniques, such as Gabor and Wavelet transform, were widely applied to analyze texture issues [4]. Gabor filters based on the human vision system, analyze input images with a set of filters and generate partial images which have different frequencies and directions. Availability of frequencies and directions in a filter bank allows for feature extraction which provides further information about image textures. Major disadvantages of Gabor filters include their high calculation process and sometimes being non-orthogonal which leads to output of filter banks having significant correlation [5]. Wavelet analysis is a suitable solution for resolving this problem which appears widely in texture analysis issues. Several methods have been proposed based on wavelet transform in order to improve surface defect detection. For example, Amet [6], has offered Wavelet transform methods and texture feature extraction using a co-occurrence matrices on the approximation image obtained from wavelet transform in order to classify defects in fabrics. Rimac [7], used Discrete wavelet Transforms in a radial basis neural network to detect defection in tiles. Ghazvini et al. [8], has proposed applying two-dimensional wavelet transform and extraction of statistical features from sub-bands and a perceptron neural network for classification of defective tiles. In spite of many advantages of Discrete Wavelet transform,

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a major problem exists is the lack of translation shift [9]. Accordingly, in this paper a suitable algorithm with high precision is used for segmentation of tile defects based on UDWT for feature extraction which is independent from shifts.

Also we combine with statistical methods such as co-occurrence matrices in order to calculate feature vectors. Finally, for classification, feed forward neural networks have been used.

II. UNDECIMATED DISCRETE WAVELET TRANSFORMS (UDWT)

A. Discrete Wavelet Transform

For applying wavelet Transforms to images, two-dimensional wavelet transform should be used [10]. So, one-dimensional wavelet transform are applied on rows and columns of image matrices seperatly to achieve the two-dimensional transforms.

Let us consider an image I(n,m) of size N×N. Firstly, two filters $H_O(z)$ (low pass filters) and $H_L(z)$ (high pass filters), are applied to the rows of I and then down sampled by a factor of 2. In this phase, two images are produced which respectively contain low and high frequencies of I with size of N/2×N. In the next phase, the filters are reapplied along the columns, followed by decimation by a factor of 2. Ultimately, four sub-images which have label of LL, LH, HL, HH have been created. This process has been shown in Fig (1).

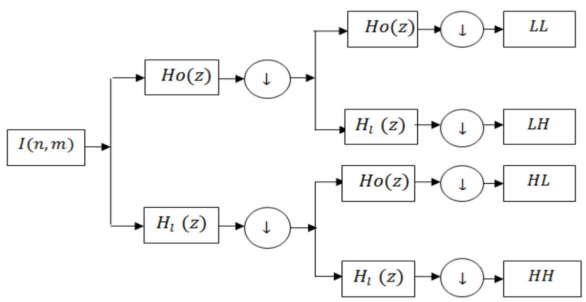

Fig 1. Wavelet Transforms of an image in two scales

B. Properties of Discrete Wavelet Transform

Wavelet analysis is an effective tool, because it allows the extraction of separate (discriminative) events which are representatives of the image [11].

Furthermore**,** calculation of Discrete Wavelet Transform by using filters in both horizontal and vertical directions, as we said in the previous section, makes it possible to separate some specific frequency events. High pass filters emphasize high frequency events, like edges. Accordingly, their combinations with row and column directions give some interesting results such as HH, HL and LH sub-bands. Therefore, this method is used for suitable feature extraction which has defect rotation on the texture surface. Discrete Wavelet Transform is a powerful tool for elimination of noise from image backgrounds in LL sub-bands too [12].

Discrete Wavelet Transform are scale invariant [12]. Therefore, scale of the input image will be matched by using corresponding functions on the original image.

However, despite the aforementioned benefits, it has one main drawback: it is shift variant. Therefore, one defect in different places in a texture image creates differences and finally leads to different defect detection.

C. UDWT

One of the main different species for standard Wavelet transform (DWT) is Undecimated Discrete Wavelet which has multiple other names including statistics, additive, and independent DWT [13]. Typical and standard definition of UDWT 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: Mallat algorithm [14] and a Trous algorithm [15].

In this paper, Trous algorithm has been used because of its simplicity compared to Mallat. This algorithm is as the same as DWT except for the lack of down sampling for the coefficients of Wavelet Transforms. Instead it up-samples the high pass and low pass filter of the wavelet by inserting zeros between each sample. Fig 2 Demonstrates the process of UDWT. In this image, if H_0 (H_1) was a response of low pass or (high pass) filters in level one, and then filters in level "J" have a response of H_0 (H_1) with $2^{j-1}-1$ zeros which are inserted among each component.

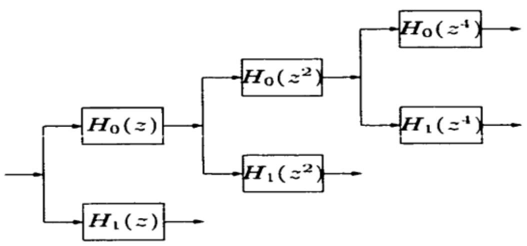

Fig 2. Undecimated Discrete Wavelet Transform

III. GRAY LEVEL CO-OCCURRENCE MATRICES (GLCM)

A co-occurrence matrices is a square matrices whose elements correspond to the relative frequency of occurrence of pairs of gray level value of pixels separated by certain distance and direction. Above all, co-occurrence matrices elements G×G, P_d are determined with distance vector for d=(dx,dy) as follow:

$$P_d(i,j) = |\{((r,s),(t,v)) : I(r,s)=i, I(t,v)=j\}| \qquad (1)$$

Which, I(.,.) shows an image with size of N×N with G gray level as following:

$(t,v) = (r+dx, s+dy), (r,s), (t,v) \in N \times N$ and $|\{((r,s),(t,v)) : I(r,s)=i, I(t,v)=j\}|$ as the absolute value. After calculation of the co-occurrence matrices, the next step is extraction of texture features which are obtained from applying suitable functions on "p". In this field, Haralick [16] introduced 14 measures of textural features which are derived from the co-occurrence matrices and in this paper, four measures have been used, such as:

$$ENT = \sum_i \sum_j p(i,j) \log p(i,j) \quad (2)$$

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

$$CON = \sum_i \sum_j (i-j)^2 p(i,j) \quad (3)$$

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

$$ASM = \sum_i \sum_j \{p(i,j)\}^2 \quad (4)$$

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

$$IDM = \sum_i \sum_j \frac{1}{1+(i-j)^2} p(i,j) \quad (5)$$

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

IV. PROPOSED ALGORITHM FOR DEFECT DETECTION

The aim of the proposed method in this research is the segmentation of defects from images with the combination of the co-occurrence matrices and undecimated wavelet Transforms. The approach to texture defect classification is twofold: Feature extraction and classification of feature space.

A. Feature extraction

According to an image of I(n,m), we consider the following steps for feature extraction.

Step1) Application of UDWT algorithm based on the above mentioned definitions in section II(C) and decomposition of images to four sub-bands I_{LL}, I_{LH}, I_{HL} and I_{HH} by using wavelet filter coefficients.

Step2) Calculation of energy for each sub-band and comparison with the maximum amount of energy and then inspection of the remained sub-bands for the following phases.

Step3) Dividing the image into non-overlapping windows with size “w”.

Step4) Calculation of the matrices event P for d = 1 (the distance between pairs of pixels) and angles (0, Π/8, Π/4, 3Π/8, Π/2, 5Π/8, 6Π/8, 7Π/8, Π) on each window.

Step5) Extraction of four features based on ENT, CON, ASM and IDM based on available relations.

Step6) Repetition of above mentioned steps for all sub-bands and produce of feature vector.

B. Classification Technique

After extraction of feature vector, classification of feature spaces is carried out to evaluate whether or not each window is normal or defective. Different techniques are available, however, in this paper; back propagation neural networks are used.

1. Error back propagation algorithm

This algorithm is a reduced recursive gradient algorithm which is used in training multilayer neural networks, generally called multi-layer perceptron networks (MLP). The processing of back propagation algorithms are composed from two main paths: the forward path and backward path.

In the forward path, a training pattern is applied to networks and its influence spreads through the middle layer to the output layer and ultimately the exact layer of network is obtained. It is noteworthy in that this path, network parameters such as weight matrices and bios vectors are constant and unchanging.

In the backward path, network parameters correct based on error correction law. In other words, after the weight matrices and bios vectors we can minimize error amount. This algorithm first uses an arbitrary amount for weights to reach the least error.

V. DATASET AND EXPERIMENTS

The used database involves approximately 250 images from 4 types of tiles with different patterns and 80% of images are defective, leaving 20% as normal. Fig (3) shows a normal specimen of 4 types of tiles. In order to experiment and justify of proposed algorithm, some regulation of parameters is done. In the feature extraction segment, first, in order to analyze the image to the sub-bands by UDWT method, the Bspline (2/2) of biorthogonal filter coefficient has to be used. Table 1 shows the wavelet coefficients of Bspline (2/2). Then, before the calculation of co-occurrence matrices, sub-bands of images are quantized to 256 levels (8 bits). The size of non-overlapping of windows has been selected based on image precision and types of texture. In this paper, windows with 14×14 are used. The reason of using this method is that the best algorithm operation for segmentation of 7×7 is obtained based on Amet’s research [6]. Since there is no down sampling and image dimensions for UDWT experiments are done with double the window size for standard wavelet transform. In classification, 70 percent of samples are selected for training and 30 percent of the remained samples are selected for network tests. For evaluation of the classification used, Three criteria such as SNS, percentage of displayed defect pixels and SPC, and percentage of displayed true pixels and ultimately total precision are obtained from an average of these two criteria($(SNS+SPC)/2$). Table 2 and Table 3, respectively represent the results of proposed method and basic method [6] (combined of Discrete Wavelet Transform and GLCM).

As it is shown in Table 2, tiles sorted as “A” are segment at best with accuracy of 96.57% and tiles sorted as “D” at worst with accuracy of 81.53%. This data shows an increase of precision compared to Table 3. Fig 4 shows the result of segmentation of surface defects which are obtained from both methods. Also Fig 5 represent the precision rate through a chart.

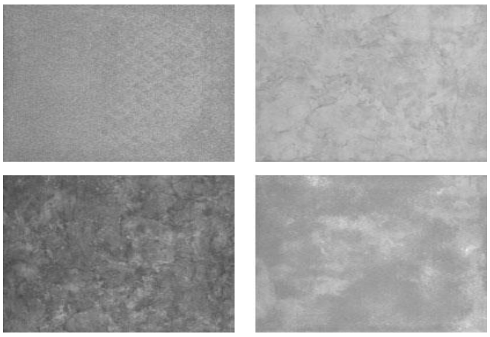

Fig 3. Normal samples of four types of tiles

Table1

Filter coefficients of BS (2/2)

N	Low pass filter	High pass filter
1	0	0
2	-0.1768	0.3536
3	0.3536	0.7071
4	1.0607	0.3536
5	0.1768	0

Table 2

Results for proposed method

	%SNS	%SPC	%Precision
A	93.47	99.67	96.57
B	81.95	98.21	90.58
C	87.02	99.41	93.21
D	87.69	97.20	92.44
Average	87.53	98.62	93.20

Table 3

Results for basic method

	%SNS	%SPC	%Precision
A	90.45	99.50	94.47
B	78.45	98.10	88.27
C	83.89	99.20	91.54
D	84.03	97.12	90.57
Average	84.20	98.48	91.21

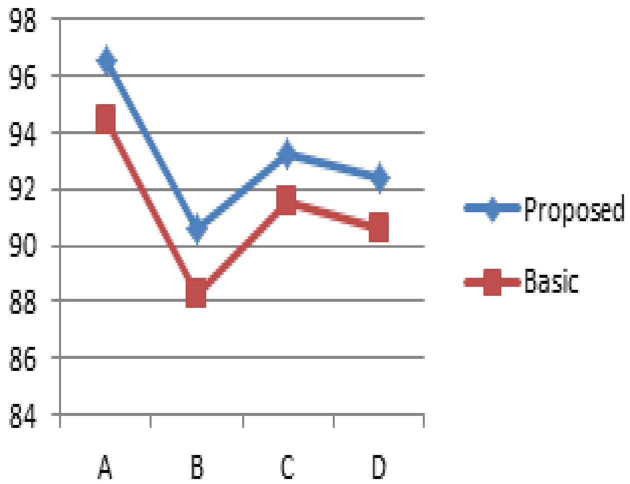

Fig 5. Precision rate comparison chart between basic method and proposed method

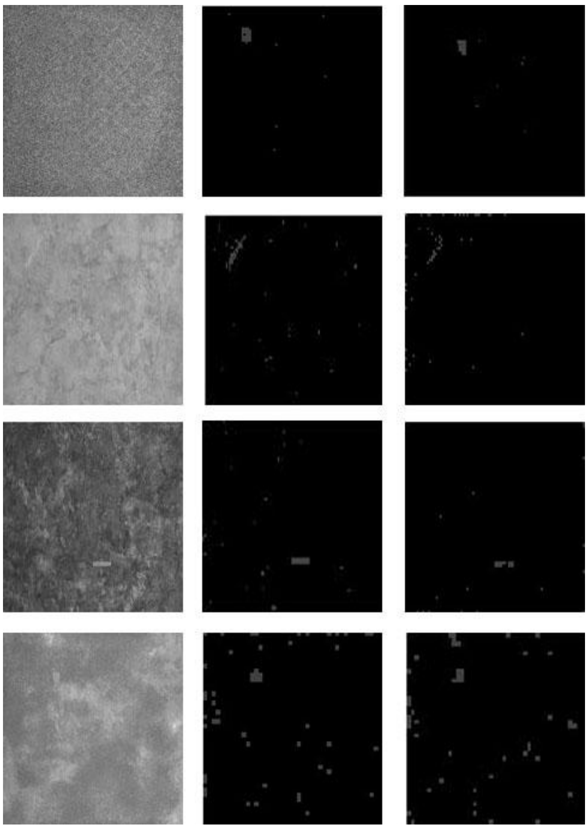

Fig 4. (1) Images of defect surfaces tiles (2) Defect detects through proposed method (3) Defect detects through basic method

VI. Conclusion

In this paper, a new method for segmentation of tile surface defects with random textures is represented. In this method, Undecimated Discrete Wavelet Transform is employed in order to extract defect frequency features. Then the outcome is applied to a co-occurrence matrices on sub-bands which have high energy for texture characteristics extraction.

Finally, we uses back propagation neural networks for defect segmentation. The motivation for using the neural network is to obtain greater efficiency when compared to other classification methods. Results of experiments show that this method has a higher accuracy than a typical Wavelet transform method and co-occurrence matrices.

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