ISA Transactions 53 (2014) 834–844

Contents lists available at ScienceDirect

ISA Transactions

journal homepage: www.elsevier.com/locate/isatrans

Research Article

Surface defect detection in tiling Industries using digital image processing methods: Analysis and evaluation

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ARTICLE INFO

Article history:
Received 17 June 2013
Received in revised form
21 October 2013
Accepted 21 November 2013
Available online 4 February 2014
This paper was recommended for publication by Mohammad Haeri

Keywords:
Surface defect
Tiling
Pattern recognition

ABSTRACT

Ceramic and tile industries should indispensably include a grading stage to quantify the quality of products. Actually, human control systems are often used for grading purposes. An automatic grading system is essential to enhance the quality control and marketing of the products. Since there generally exist six different types of defects originating from various stages of tile manufacturing lines with distinct textures and morphologies, many image processing techniques have been proposed for defect detection. In this paper, a survey has been made on the pattern recognition and image processing algorithms which have been used to detect surface defects. Each method appears to be limited for detecting some subgroup of defects. The detection techniques may be divided into three main groups: statistical pattern recognition, feature vector extraction and texture/image classification. The methods such as wavelet transform, filtering, morphology and contourlet transform are more effective for pre-processing tasks. Others including statistical methods, neural networks and model-based algorithms can be applied to extract the surface defects. Although, statistical methods are often appropriate for identification of large defects such as Spots, but techniques such as wavelet processing provide an acceptable response for detection of small defects such as Pinhole. A thorough survey is made in this paper on the existing algorithms in each subgroup. Also, the evaluation parameters are discussed including supervised and unsupervised parameters. Using various performance parameters, different defect detection algorithms are compared and evaluated.

1. Introduction

Nowadays, ceramic and tile industry represents one of the most dynamic industries, including lots of innovations in various stages of production and automation. However, human vision control is still used for detection of defective products and grading and automatic grading is not yet well established [1]. Grading is implicitly related to the whole fabrication line because various surface defects such as color, image pattern, crack or scratch, arc, and bumps on the ceramic or tile originate from different stages [1]. The main challenge of automatic grading is in the image processing algorithms required for defect detection. Different challenges of grading are namely various kinds of color, different kinds of texture design, real-time processing requirement and the vast types of defects [1]. Current grading is usually done in three stages: first, tile arc is measured by a linear planer; then, size difference compared to ideal size is measured by a stacker; finally, surface defects are identified by human vision and registered on the product surface with fluorescent markers. This traditional and non-automatic grading process suffers from problems such as poor performance, non-repeatable procedure, high cost, and low speed. Industrial and unhealthy environment of product line for humanitarian personnel is another negative factor of manual grading.

The automatic grading system would result in better performance, lower cost, and uniformity in each category of products. The current increasing demand of tile and ceramic validates the market need of automatic grading for higher production speeds [2]. In modern production lines, tiles are actually classified into five grades based on the three above mentioned evaluation criteria, in which level five is considered as losses [3].

Up to now, various processing algorithms have been proposed for intelligent grading. These methods can be divided into four main categories according to the defect detection mechanism: filtering methods, structural techniques, statistical methods, and model-based techniques (Table 1). Filtering methods usually use mathematical translation and filters or pattern recognition methods for defect detection. The structural approaches consist of conventional morphological image processing and edge detection algorithms. Model-based approaches include common image

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0019-0578/$ - see front matter
http://dx.doi.org/10.1016/j.isatra.2013.11.015

Table 1
Different approaches of defect detection.

Approach	Processing algorithm	References
Filtering methods	Wavelet transform	[12–18]
	Countorlet transform	[19–21]
	Genetic algorithm	[22–26]
	ICA algorithm	[27–30]
	Neural networks	[32–35]
	Gabor filter	[36–38]
Structural algorithms	Morphology	[39–47]
	Edge detection	[7,11,48–51]
Model based techniques	Hidden Markov model	[59–61]
	Autoregressive model	[62–65]
Statistical methods	Histogram curve	[66,67]
	Co-occurrence matrix	[68–76]
	Weibull distribution	[77–82]
	Autocorrelation	[83,84]

processing models like the Auto-Regressive (AR) and Hidden Markov Models (HMM). In the statistical approaches, luminance histogram is generally used for defect detection. Statistical methods are characterized by simplicity as well as low complexity [4].

Because of various chemical and mechanical processes in the ceramic tile production line, diverse types of surface defects appear on the final product. The defects generally have different visual patterns which are sometimes contradictory. Therefore, the desired grading system should include a variety of image processing algorithms to cover different types of surface faults or defects.

In this paper, the proposed algorithms for grading system in ceramic and tile production line are discussed and evaluated in terms of output quality and computational complexity. In Section 2, different types of surface defects appearing in the fabrication lines of ceramic and tiles are studied. In Section 3, different defect detection algorithms are discussed. Then, Section 4 deals with the evaluation parameters. Firstly, available measures described for evaluating defect detection algorithms are presented. Using quality parameters, proposed techniques are compared. Finally, the discussions are concluded in Section 5.

2. Surface defects of ceramic and tiling

Ceramic and tile products pass various chemical and mechanical stages through the production line. Production of ceramic tiles comprises eight main stages: forming, drying, glazing, baking, grading, and sorting [92] as shown in Fig. 1. Glazing defects occur in glazing and printing stages. Defects that are associated with breaking and cracks happen in the forming and baking stages. In contrast, edge defects are caused more by the transmission process from glazing lines to kiln. Also, the Pinhole defect occurs typically in kiln [3].

Accordingly, surface defects can be divided into six categories with the following characteristics (Fig. 2) [5].

- Pinhole
  Pinhole is a quality fault appearing as small holes on the product surface. Pinhole sizes are typically less than one millimeter. Also, the holes appear with a lumber and depression. This fault typically occurs during baking.
- Eclipse glaze
  This problem originates from accumulation of a part of glaze over a corner or part of the tile. Accumulation of glaze is usually on a few millimeters with significant expansion in the region of defect. This defect appears in the glazing stage by creeping and ringing of the glaze [5].
- Crack
  The most common defect is the crack which occurs because of fast baking procedure with rapid increase or decrease in temperature. Cracks at the edges of the tile are mostly caused due to increasing temperature. Cracks due to decreasing temperature are also called air cracks or cold cracks and often occur because of fast baking procedure in the kiln [6].
- Blob
  Some patches like spot drops of water may exist on the tile surface, and are called blob defects. It occurs if humidity is not adjusted or a low sleep time is included before entering into the kiln.
- Scratch
  This failure occurs because of dragged color printing in some directions. This defect is often created during the transmission of products from glazing line to the kiln.
- Edge
  Edge defects occur most commonly in the kiln but they may be generated from other manufacturing stages [7–9].

3. Algorithms of defect detection for ceramic and tile products

For the detection of surface defects, it is required to analyze the whole product surface. So, an image with high resolution should be firstly captured. The system must have appropriate lighting to obtain a suitable surface picture. According to Table 1, the defect detection algorithms may be classified into four principal groups. Here, the main algorithms of each group are discussed.

3.1. Filtering approaches

In the filtering approaches, mathematical transformations and filters are generally used. In this regard, both linear and nonlinear transforms may be used. The most important algorithms include the Wavelet and Counterlet transform, Independent Component Analysis (ICA) analysis, Gabor filtering and artificial neural networks which are discussed below.

3.1.1. Wavelet transform

According to the nature of multi-resolution analysis, wavelet transform has been extended for many processing applications and is sometimes known as the most powerful tool [10,11]. In wavelet transform, two low-pass h and high-pass g filters called father and mother functions, respectively, are used in a filter bank way (Fig. 3) [12]. In Fig. 3, the input is an $n \times m$ image and there are also four outputs of LL, LH, HL and HH with size $(n/2) \times (m/2)$. At each stage, the input image is divided into four sub-images.

Wavelet transform has been used for pre-processing and texture feature extraction [13]. In 2001, Kumar and Pang proposed a method of defect detection based on wavelet packet. There, the wavelet packet coefficients from a set of dominant frequency channels containing significant information are used for the characterization of textured images. This method is useful in very soft texture changes [14]. In 2005, Yang et al. applied a similar method to inspect the fabrics in textile factories for defect classification using discriminative wavelet frames. For a better description of the latent structure of the textile image, adaptive wavelet frames for textile would be preferred rather than standard ones. The challenge in this method is how to select the wavelet. Also, the training stage is so dependent on the number of data points [15].

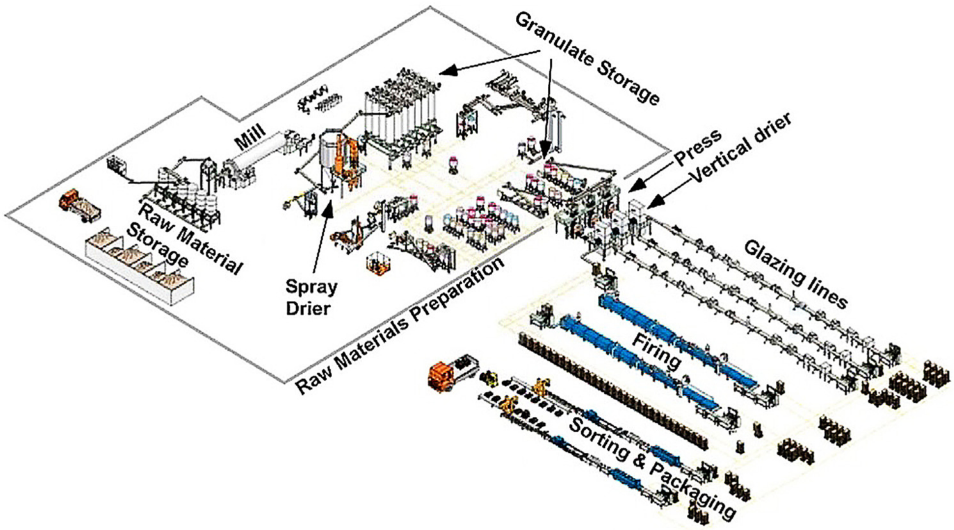

Fig. 1. General stages of fabrication in ceramic and tile factory [93].

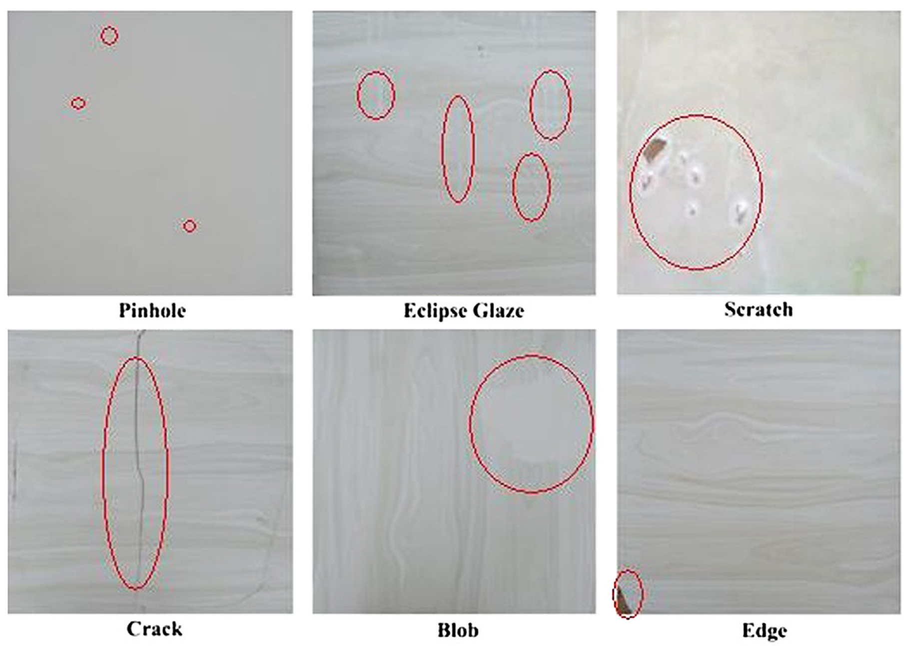

Fig. 2. Types of surface defects on the ceramic and tile products.

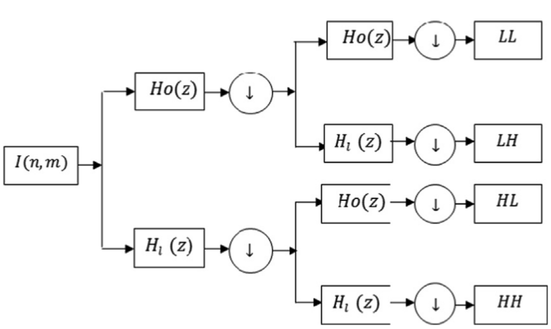

Fig. 3. General realization of wavelet transform in image analysis.

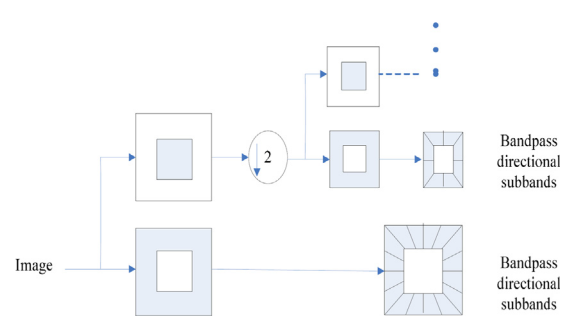

Fig. 4. General block diagram of contourlet transform.

3.1.2. *Contourlet transform*

Contourlet transformation based originally on the wavelet transform aims to overcome the weakness of selected wavelet type [16]. Contourlet transformation exploits multi-resolution and space-frequency curve like the Wavelet. Contourlet transform combines pyramid laplacian with a direct two-dimensional filter-bank (Fig. 4). The band-pass image is converted to eight sub-images from pyramid laplacian. This transform has good performance for denoising and enhancing the picture [17].

In 2012, Ai et al. introduced a new method of feature extraction based on the contourlet transform and kernel locality preserving projections to extract sufficient and effective features from metal surface images. In this study, the image information at certain direction is important for the recognition of defects, and the contourlet transform is introduced for its flexible direction setting. The disadvantage of this method is a need for extra information of contourlet transform. However, the total classification rates of surface defects of continuous casting slabs and aluminum strips are up to 93.55% and 92.5%, respectively in this work [18].

3.1.3. *Genetic algorithm*

Genetic algorithm can find a suboptimum solution for optimization and searching problems [19,20]. In the context of defect detection, a statistical relationship is firstly considered to determine the pixels corresponding to surface defects. Then, the related parameters are considered as genes and genetic algorithm optimizes these parameters. Those parameters may represent thresholding point or morphological method parameters [21,22].

In 2002, Zheng et al. introduced a method based on the genetic algorithm to detect surface detects. In this algorithm, morphological parameters have been used including base element and thresholding points. Though, this method is very simple, but the training stage remains a controversial challenge [23].

3.1.4. *ICA*

ICA algorithm is a basic method of source separation [24,25]. In image processing applications, the ICA algorithm generally supposes that the input image is combined of two or more independent images. ICA algorithm tries to find the elementary images. In defect detection, defects are supposed to be on a foreground mixed with background pattern. Then, ICA is used to separate the foreground from the background [26–28].

In 2006, Tsai et al. proposed a defect detection method based on ICA. They used a constrained ICA model for designing an optimal filter to detect surface defects from noiseless background. The proposed algorithm requires to have defectless pattern. Also, the performance degrades in the presence of noise [27].

3.1.5. *Artificial Neural Networks*

Artificial Neural Networks (ANN) are mostly used in machine learning and artificial intelligence [29,30]. In image processing and defect detection systems, neural networks are used as the classifier. Therefore, it is necessary to extract feature vector before applying any image to the neural network. In defect detection, feature vectors would be classified into two classes of defectless and defective patterns by ANN [31]. In 2008, Suyi et al. proposed an ANN for defect detection in textiles [32]. Neural networks have some defects, namely, the related training process takes long time, easily trapped in local minima, which influence the accuracy of the algorithm. Whereas particle swarm optimization has good search ability, but in this work the Particle Swarm Optimization–Back-Propagation (PSO-BP) algorithm is used for the neural network which has a fast training stage rather than the BP algorithm.

3.1.6. *Gabor filter*

Gabor filters are the ones which have the same representation in the spatial and frequency domains. These filters can be obtained from combining an exponential and a Gaussian function as follows [33]:

$$G(x,y) = e^{-\pi\left[\frac{(x-x_0)^2}{\alpha^2}+\frac{(y-y_0)^2}{\beta^2}\right]} \times e^{-2\pi j[u_0(x-x_0)+v_0(y-y_0)]} \tag{1}$$

where x_0, y_0 is the center of the receptive field in the spatial domain and u_0, v_0 stands for the center of the filter in frequency domain. σ and β represent the standard deviations of the elliptical Gaussian along x and y. Although Gabor filters are not orthogonal, they cover complete information of the image and are able to choose a specified frequency and direction.

In surface defect detection applications, defects may be discriminated by applying Gabor filters, after a simple thresholding can result in the defect regions [34]. Therefore, the Gabor filter is used mostly as a pre-processing stage. In 2010, Che et al. introduced a method for fabric defect detection in textile industry based on change in the scale of the Gabor filter. Their proposed method suffers from high computational complexity. Besides, this method requires a reference defectless image [35].

3.2. *Structural approaches*

In structural methods, primary and hierarchical forms are used for defect detection leading to an intuitive procedure and comprehensible computations. These approaches use morphological operators as well as edge detection methods for defect detection.

3.2.1. *Morphological methods*

Morphological operators are methods for both binary and grayscale image processing based on morphology. The output value of each image pixel is determined with respect to the input pixel value and its neighbors [36–38]. In all morphological processings, structural elements are used. So, the appropriate choice of this element is often the most important part of the process [39]. Closing operator causes some regions of the image to smoothen, which usually mixes the thin fracture and removes the small holes, and fills up the track in the environment [40].

Morphological operators are usually used for improving, smoothing, and noise reducing in defective images. Also, by using morphological operators, edge detection in defective images is realized [41–43].

In 2009, Yiu et al. proposed a new method based on morphological operators to detect defects in fabric texture. In this method, Gabor wavelet was firstly used to design the base element of morphological methods (learning phase). The algorithm works so that the input image successively passes through opening, closing, median filter, closing, and thresholding stages and the defect in the output image is indentified. This method is of supervised type and accounts for specific defects [44].

3.2.2. *Edge detection algorithms*

Edge is defined as a boundary between two dissimilar regions of an image. There are many different methods for edge detection [5]. One of the simplest methods for the edge detection is the gradient of image [45,46]. Thresholding is the last stage in edge detection. The edge of an image can be achieved with high accuracy by choosing appropriate threshold [47]. Edge detection methods are used for the detection of edge defects in the surface defect detection and image segmentation [48]. In 2011, Salimian and Pourghassem proposed a method for detection of edge defect in ceramic and tile. In this method, edges are firstly detected using the canny algorithm. Then, the angle of corners is determined by using inner product. Finally, the corner is considered as a defective edge if the angle is about 89–92° [9]. In 2006, Mukherjee et al. introduced an edge density-based technique for defect detection and an object-based coding approach has been applied for the storage of defective ingots. For extracting the edge density, they used the Discrete Cosine Transform (DCT). After detecting the boundary of ingots, the defect on the ingots surface is detected by using a texture decoder that is based on the Gaussian filter. This technique suffers from low speed as it requires the employment of small blocks [49].

3.3. Model-based approaches

In model-based image processing, a model is selected to analyze the image and the model parameters are desired unknowns. It includes the Hidden Markov Model (HMM) [50]. In HMM, the model can be imagined as a set of interconnected states which are connected by a series of probability lines [51]. Other model-based methods are limited interval [52], Autoregressive Model (AR) [53–56], and the Fractal Model [57].

3.3.1. Hidden Markov model

Here, a unique state would be allocated to each feature. Usually some images are used to train the HMM. To train the HMM, algorithms such as Back-propagation, Forward-propagation, Viterbi and Back-Forward propagation can be noted [58,59]. If Hidden Markov Models are used for defect detection, three components of states, vector π and state transfer matrix must be defined. Occurrence probability of defective or defectless state in the zero region of image is expressed as vector π. It must be reminded that each $N \times M$ small region of the image is considered as one state where N and M represent the size of the region. Probability of state variation from defective manner to defectless condition (or vice versa) is shown by state change matrix. In 2008, Hadizadeh and Shokouhi introduced a method of defect detection using 1-D HMM. In this method, the input image is predicted by HMM. Then, the difference between the model output and input image exhibits defects [49]. One of the main problems in this method is related to the complexity of statistical computation.

3.3.2. Autoregressive model

AR models including the thresholding autoregressive model and exponential autoregressive model [60] represent a simple model-based methodology [61,62]. After the determination of AR model parameters for the desired texture, the specific regions of texture which are incompatible with the model parameters can be considered as defect regions.

In 2010, Bu et al. presented a method based on new spectral analysis approaches of time series for defect detection on the fabric texture using AR spectral estimation based on the Burg-algorithm [63]. Also, a training phase is required and non-deterministic and statistical results are disadvantages of this method.

3.4. Statistical approaches

Statistical methods are often used in classification problems. The main methods include histogram curve properties, fitted Weibull, co-occurrence matrix, and autocorrelation.

3.4.1. Histogram curve

Image histogram describes the number of pixels at each luminance level in the input image. Fig. 5 illustrates a defective image and its histogram. If an optimal threshold point in the image histogram is considered, the defect pattern can simply be extracted by thresholding [64].

In 2006, Hui-Fuang Ng proposed a thresholding scheme applied to histogram for defect detection. This method is based on the Otsu method and calculates the suboptimal point (Valley emphasis) in the histogram curve for defect detection. It corresponds with an easy implementation, but sometimes results in large error (divergence) [65].

3.4.2. Co-occurrence matrix

Haralick and colleagues used adjoining matrix to study the properties of different textures [66]. Gray Level Co-occurrence Matrix (GLCM) has some information about relationships between neighboring pixel values in an image which is mathematically given as

$$C_{\Delta x,\Delta y}(i,j) = \sum_{p=1}^{n} \sum_{q=1}^{m} \begin{cases} 1 & \text{if } I(p,q)=i \text{ and } I(p+\Delta x, q+\Delta y)=j \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

where C is the co-occurrence matrix and I is a $N \times M$ image, Δy and Δx are distance and direction parameters, respectively [67,68]. Co-occurrence matrix can be created in any direction and distance for feature extraction by selecting the distance and direction parameters. Usually the co-occurrence matrix is used in six directions for feature extraction and defect detection [69]. But in some cases only two directions of the co-occurrence matrix are used for defect detection applications [70]. GLCM is used to extract features such as entropy, contrast, angular second moment, correlation, and inverse difference moment [71–73].

- Entropy

$$\mathrm{EN} = -\sum_i \sum_j C(i,j) \log\, C(i,j) \quad (3)$$

Entropy is defined as the complexity of the image. The more complexity in the texture, the greater the value of entropy.

- Contrast

$$\mathrm{CON} = \sum_i \sum_j (i-j)^2 C(i,j) \quad (4)$$

Contrast of an image determines the amount of local variations.

- Angular Second Moment (ASM)

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

Angular second moment is a measure of image homogeneity. Hence it is suitable for measurement and diagnosis of texture disorders.

- Inverse Difference Moment

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

- Correlation

$$\mathrm{COR} = \frac{\sum_i \sum_j i \times j \times C(i,j) - \mu_x \mu_y}{\sigma_x^2 \sigma_y^2} \quad (7)$$

where the parameters in this equation are as follows:

$$\mu_x = \sum_i i \sum_j C(i,j) \quad (8)$$

$$\mu_y = \sum_j i \sum_i C(j,i) \quad (9)$$

$$\sigma_x = \sum_i \sum_j (i-\mu_x)^2 C(i,j) \quad (10)$$

$$\sigma_y = \sum_i \sum_j (j-\mu_y)^2 C(i,j) \quad (11)$$

where μ_x, μ_y and σ_x, σ_y are mean and variance of rows and columns of GLCM, respectively.

In 2012, Mingde et al. proposed an algorithm based on the Support Vector Data (SVD). In this method, two GLCMs are firstly

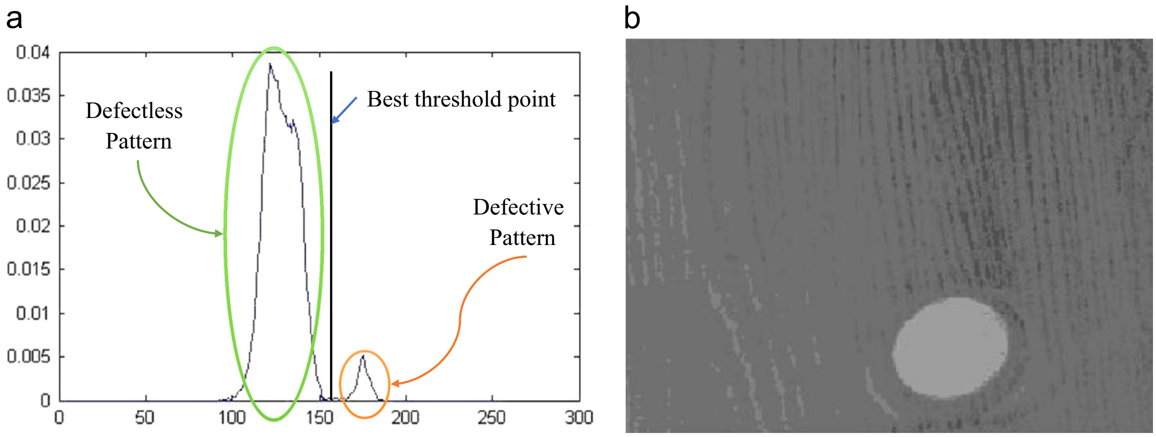

Fig. 5. A defective tile pattern with its histogram: (a) histogram curve (b) defective tile surface.

created to describe the fabric texture. So an adaptive quantization is applied to GLCMs for reducing the complexity of computing in GLCM. Next, SVD is used for classifying as a classifier. This algorithm is suitable for real-time applications [74]. Complex calculation to obtain the feature vector is a disadvantage of the method whereas using a simple linear classifier is due to accelerating classification.

3.4.3. Weibull distribution

Recent studies show that a random texture can be analyzed by using a Weibull distribution [75]. In addition, most works show that the image Weibull distribution has accurate results for unsupervised image segmentation and classification. Also the distribution has been used for visual content analysis [76,77]. Weibull probability density function is as follows [78]:

$$f(x)=\frac{\gamma}{\beta}\left(\frac{x}{\beta}\right)^{\gamma-1}e^{-\left(\frac{x}{\beta}\right)^{\gamma}} \tag{12}$$

where β is distribution width that in fact represents image contrast, and γ is the distribution peak that represents the size of image seeds. A Weibull distribution can fit image derived distribution. In this case, lower amount of β parameter would result in lower image contrast. Meanwhile, low value of parameter γ is a symbol of coarse or rugged texture in an image. Also the equation is defined for $x>0$ [75]. Fig. 6 illustrates four examples. In this figure, the first column is the input image, second column is derivation amplitude, third column is histogram of derived image, and the fourth column is fitted distribution. In this figure, specially-selected images have been used instead of practical tile images to better evaluate the algorithms in absence of noise from the viewpoint of capability of defect pattern extraction. Also, the test images are associated with specific histograms to cover all possible situations.

For defect detection in the texture, first, the image is divided into same pieces and the gradient amplitude is calculated for each piece. Next, histogram of image gradient is calculated, and finally, the last stage includes a Weibull distribution fitting to the histogram of the image gradient. With the obtained distribution parameters and considering them as arrays of the feature vector, the defect can be detected by a distance scale. Fig. 7 illustrates these stages [74]. Moreover, the expectation maximization method can be used for calculation of distribution parameters [79,80].

In 2011 Fabian Timm and Erhardt Barth proposed a non-parametric approach for defect detection which uses only two features. The advantage of this method is fast clustering because it uses only two features, but at the same time, feature vector generation includes complex calculation such as image derivation and distribution parameters fitting [74].

3.4.4. Autocorrelation

In fact, autocorrelation of an image represents the similarity among image pixels. The autocorrelation method checks the correlations between image pieces and patterns in image processing [81]. In 2010, Hoseini et al. exploited the autocorrelation function as a tool for defect detection. This method has four stages. In the first step, the original texture pattern is extracted from a defectless image (training stage). In the second step, global defective region is described as the difference between reference and input texture patterns. Third stage calculates the mean of the image for decreasing high frequency information from the image background. In the last step, the defect is detected using thresholding [82].

4. Evaluation of defect detection methods

4.1. Evaluation criteria

Different criteria may be used to evaluate various detection methods including error definition and percentage of defect detection diagnosis or misdiagnosis. For calculation of error, a measure of correct diagnosis should be considered to evaluate different algorithms output. In this case, the defect is generally detected by the human vision and the related pattern is defined for evaluation purpose. Fig. 8 illustrates a defective tile image and its defect pattern image that is created by human vision [83].

It should be reminded that the supervised evaluation method is a subjective and relative method [84]. Parameters for the supervised evaluation method include Figure of Merit (FOM) [85], Hausdorff Distance [86], and Odet's criteria (ODI and UDIn) [87].

- Figure of merit

$$\mathrm{FOM}(I_t,I_s)=\frac{1}{\max\{\mathrm{card}(I_t),\ \mathrm{card}(I_s)\}}\sum_{i=1}^{\mathrm{card}(I_s)}\frac{1}{1+d^2(i)} \tag{13}$$

where in this equation, $d(i)$ is the distance between the ith pixel of image I_s, and the nearest pixel from image I_t. Also *card* (I) is the number of pixels in image I.

- Hausdorff distance

This criterion shows the distance between two sets of pixels. Equation of this criterion is as follows:

$$H(I_t,I_s)=\max\{h(I_t,I_s),h(I_s,I_t)\} \tag{14}$$

where

$$h(I_t,I_s)=\mathrm{Max}_{t_i\in I_t}\min_{s_i\in I_s}\|t_i-s_i\|,\ h(I_s,I_t)=\mathrm{Max}_{t_i\in I_s}\min_{t_i\in I_t}\|s_i-t_i\| \tag{15}$$

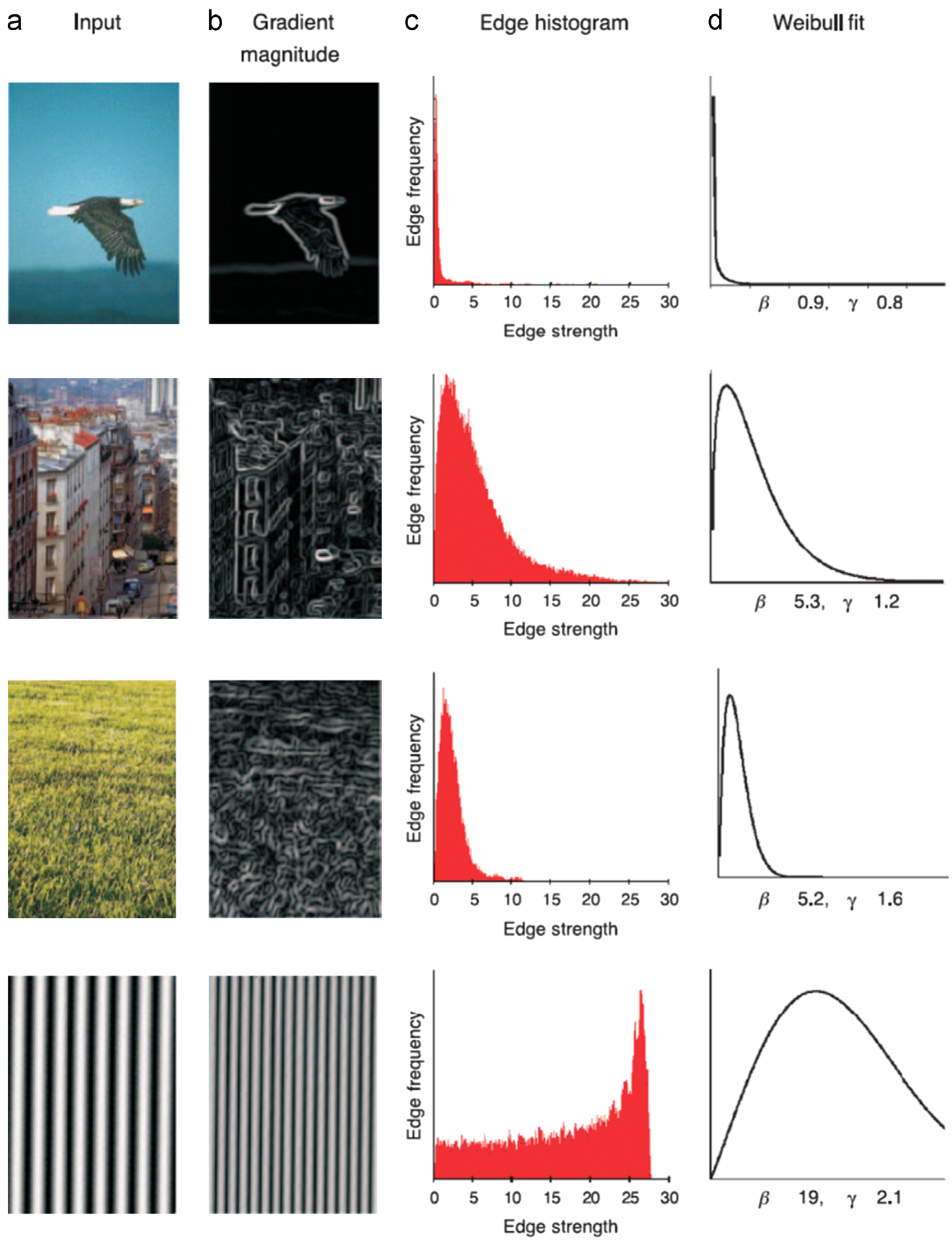

Fig. 6. Four example for fitting the Wiebull distribution.

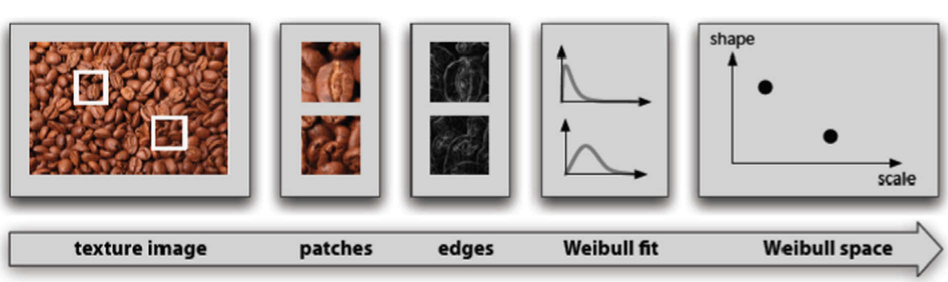

Fig. 7. Feature vector generation with Weibull distribution.

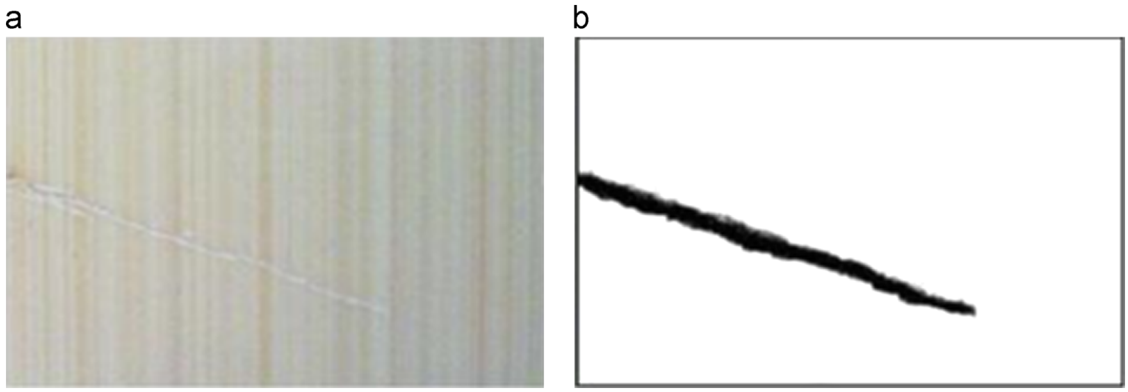

Fig. 8. (a) Defective tile image. (b) Defect pattern extracted.

Table 2
Experimental evaluation criteria associated with different defect detection approaches.

	Histogram	Neural networks	Morphological	Gabor filter	Co-occurrence matrix	Wavelet
Local error	3×10^{-4}	7.33×10^{-4}	0.0017	0.0069	0.0269	0.0039
ODE	0.5	2.7	0.9987	4.2231	1.049	1.4448
LDE	1.5	1.7	0.002	3.2231	0.049	0.4448
FOM	0.006	0.0075	0.0061	0.0463	0.0072	0.0159
Hausdorff distance	1.4142	1.4142	1.4142	11.3137	22.6274	8.4853
ODI	0.704	0.6447	0.6329	0.5613	0.5305	0.2877
UDI	0.6256	0.5537	0.1247	0.5467	0.6416	0.4729

here I_t and I_s represent the set of defects in the output image and defect pattern respectively. This is a preferred measure of similarity between two images.

- Odet's criterion
  The Odet's criterion includes two error criteria from divergence measure, which is a popular evaluation criterion.

$$\mathrm{ODI}_n=\frac{1}{N_0}\sum_{k=1}^{N_0}\left(\frac{d_0(k)}{d_{TH}}\right)^n \tag{16}$$

and

$$\mathrm{UDI}_n=\frac{1}{N_u}\sum_{k=1}^{N_u}\left(\frac{d_u(k)}{d_{TH}}\right)^n \tag{17}$$

where in these equations $d_0(k)$ is the distance between kth pixel that is detected in the algorithm output image and the nearest pixel in the defect pattern image. Also, $d_u(k)$ is the distance between the kth pixel that is not detected in algorithm output image and the nearest pixel in the defect pattern image. N_o is the number of pixels that is wrongly detected as defective pixels and N_u is the number of pixels that is wrongly detected as defectless pixels. d_{TH} is the maximum allowed distance for defects and n is a scale factor which considers different weights for different pixels according to the distance from the defect pattern image [88].

Also, error definition can be used as a criterion for algorithm evaluation. For example the Over Detection Error (ODE) can be named. The equation of this error is as follows.

$$\mathrm{ODE}(I_t,I_s)=\frac{\mathrm{card}(I_{t/s})}{\mathrm{card}(I_t)-\mathrm{card}(I_s)} \tag{18}$$

where in this equation $card(I_t)$ and $card(I_S)$ are number of defect pixels in the algorithm output image, and defect pattern image respectively. Moreover another definition $I_{t/s}$, is allocated to the number of pixels which is used in the algorithm output image as defect pixels but not in the defect pattern image. Another error that can be introduced as a criteria to an evaluated algorithm is the

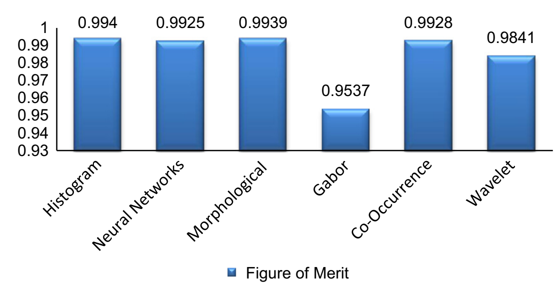

Fig. 9. FoM criterion for different detection approaches.

Lower Detection Error. This error equation is as follows:

$$\mathrm{LDE}(I_t,I_s)=\frac{card(I_{s/t})}{card(I_t)-card(I_s)} \tag{19}$$

It should be noted that in the above equation $card(I_t)$ and $card(I_S)$ are number of defect pixels in the algorithm output image, and defect pattern image respectively. On the other hand, another definition $I_{t/s}$, is allocated to the number of pixels which is used in the defect pattern image as defect pixels but not in the algorithm output image.

Another type of error is the Localized Error which is in fact the normalized number of pixels wrongly diagnosed or misdiagnosed in the algorithm output image in comparison to the defect pattern image. Equation of this error is as follows:

$$\mathrm{LE}=1-\frac{|B_o\cap B_T|+|F_o\cap F_T|}{|B_o|+|F_o|} \tag{20}$$

where B_O and F_O denote the background and foreground area pixels of the defect pattern image, and B_T and F_T denote the background and foreground area pixels in the algorithm output image [89].

FOM mostly represents experimental distance as a criterion. The closer the FOM value is to unity, the better the output quality will be. The Hausdorff distance may theoretically be a good measure for representing the similarity of two sets. However, it exhibits large

Table 3
Qualitative and quantitative comparison of different methods.

Method	Quantitative						Qualitative			
	Calculation time (PC)		Number of multiplications		Time/pixel		Real time ability	Performance	Calculation complexity	Noisy pattern
Histogram	54(ms)		512		52(ms)		Very good	Good	Very low	Good
Neural network	Train phase 13.2(s)	Test phase 112(ms)	Train phase 2540	Test phase 64	Train phase 220(ms)	Test phase 1.84(μs)	Not good	Good	High	Good
Morphology	565(ms)		0		4.64(ms)		Good	Good	Very low	Bad
Gabor	253(ms)		16		4.21(μs)		Good	Bad	Medium	Good
Co-Occurrence	5($_{min}$):39(s):19(ms)		3220		339(ms)		Very bad	Very bad	Very high	Good
Wavelet	1.242 (s)		45		20.7(μs)		Not good	Good	High	Very good

sensitivity to noise. ODI can show divergence between the over detected defect areas in the output. Similarly, UDI demonstrates the divergence of under detected areas from the defect pattern image. Hausdorff distance and the Odet criteria converge to unity as well, as the algorithms work better. These two criteria are more appropriate to detect large defects like blob, but the Odet criterion can better detect large defects such as cracks and edge defects. If the detected faults are much larger than the existing ones, error measure of ODE is more applicable. In contrast, LDE works better for the detected defects as they are smaller than the real ones. Both ODE and LDE result to zero for perfect detection. LE is a measure that compromises the performances of ODE and LDE. LE is affected by both over- and under-detection situations. It may be considered as a suitable measure for evaluating the detection of small faults such as the Pinhole defect. A lower LE measure exhibits better performance of defect detection.

Another evaluation category is the unsupervised ones which are mostly used for statistical approaches. In this case, there is no need for a-priori defect pattern image. Independence of this method from human visual detection is its advantage in comparison to the supervised methods. Nevertheless, statistical results without deterministic value can be enumerated as their disadvantage [90]. Among these methods, Entropy-based and Non-negative Factorization can be named [91–93]. In the Entropy-based method, evaluation function is based on entropy. This method uses defective and defectless regions of entropy in output image for evaluation of the algorithm. Also, outline entropy can be used for assigning the percentage of pixels belonging to each region which have been wrongly detected as defective regions. Finally, it should be reminded that there is no explicit evaluation system for diagnosis of wrong detection. Non-negative Factorization method is an evaluation measure between defective and defectless regions' contrasts.

4.2. Evaluation of defect detection methods

Different methods of defect detection are now evaluated and compared in terms of the before-mentioned performance criteria. Table 2 illustrates all these criteria for selected detection methods.

As it may be seen, local error of histogram-based methods is less than other methods, while the methods based on co-occurrence matrix have the greatest local error and appear to behave inappropriately in detecting local errors. As mentioned, over detection error demonstrates the pixels wrongly diagnosed as defective. Among the detection techniques, Gabor filters result in the largest over detection error. The histogram-based methods provide the best performance in terms of over detection error. In the case of lower detection error, the morphological operators lead to the lowest detection error. Gabor filters demonstrate worst performance in terms of the lower detection error. Three criteria of the Figure of Merit, Hausdorff distance and Odet's criteria have also been exploited. It should be noted that the better the algorithm performance, the closer to unity the measure of figure of approaches (Fig. 9).

Regarding the Hausdorff distance criterion, histogram-based, neural networks, and morphological operators exhibit the best performances and the co-occurrence matrix show the lowest evaluation.

In terms of the Odet's criteria, wavelet transform and morphological operators perform more efficiently.

5. Conclusion

This paper investigated different surface defect detection methods. Each method has its own advantages and disadvantages. Some methods have fast speed but low accuracy while other methods are associated with high accuracy but restricted by complex computations to a lower speed. According to the requirement of real-time processing and existence of different patterns in ceramic and tile industry, high speed and high accuracy are essential challenges to be afforded at the same time. Also, each method can overcome detection challenges only for some special defects. Table 3 shows a quantitative and qualitative comparison between various methods. As it can be easily seen, the histogram-based methods are distinguished by a very high speed. The histogram-based methods exhibit an independence from resolution which renders them useful in real-time applications. Low computational complexity and high efficiency are specific characteristics of the histogram-based methods. Training phase appears as a problem in methods based on neural networks, but their speed in test phase is fairly good. Morphological techniques and Gabor filters also appear to be acceptable candidates in real-time applications. In contrast, the co-occurrence technique is associated with largest computational complexity. Wavelet transform also suffers from heavy computations and is not appropriate for fast applications. In terms of robustness against noise, the best performance may be achieved using the wavelet transform and morphological techniques.

Therefore, it may be concluded that no general algorithm has yet been proposed accounting for all different defect types at the same time. So, a mixed method would be indispensable for industrial applications. It can be seen that statistical approaches are more suitable for detecting large defects such as blob. Some approaches such as the wavelet transform and Gabor filter can detect small defects like Pinhole, though they are industrially undesired due to their computational complexity. Also, structural approaches are suitable for detecting edge crack defects in ceramic and tiles. Model-based approaches are associated with complex computations, but can cover a larger extent of defects and patterns.

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