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Novel Defect Segmentation Technique in Random Textured Tiles

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Abstract— In this paper problem of detecting different type of defects on random textured tiles surfaces is addressed. Since Gabor filters allows optimal localization both in the spatial domain and in the spatial-frequency domain it is been utilized in the proposed technique to extract texture features which are useful for detecting defect edges on the tile. Kohonen's Self-Organizing Maps (SOM) is used for reducing the feature vectors to obtain 1-dimensional feature map (scalar image). The output of the SOM is smoothed with Gaussian filtering mask and Canny's edge edge-detection method is applied to the smoothed feature map image to obtain the edge map of the detected defect from the tile surface. The results obtained when the proposed technique is tested on various random texture tiles confirm its efficiency.

Index Terms— Detection of defect, Gabor filters, Self-Organizing Map, Canny operator.

1. Introduction

Automated visual inspection of industrial product has been received many attention nowadays. One of the industrial fields where an automated visual inspection for surface defect detection is most needed at the final stage of manufacturing process is the tiles manufacturing industry. The goal of the automatic surface defect detection is to insure detection sensitivity with at least the same accuracy as the human visual inspectors. A lot of efforts have been made in the field of research on automatic techniques to detect various defects such as cracks, scratches, holes/ pitting, and lumps in random textured tiles. Numerous approaches to address the problem of detecting defects in ceramic, marble and granite tiles have been reported in literature [1], [2], [3], [4], [5]. All these methods have a limited range of application for some kind of tiles and defects. Recently, method based on multi-scale and multi-orientation such as Wavelet Transform and Gabor filters has been successfully and widely used in the detection of various classes of defects and related applications in textured images [6].

Following Mallat propositions on the use of pyramid structured wavelet transform for texture analysis [7], [8] several studies have been carried out on texture analysis using wavelet transform [9], [10], [11]. As the Wavelet transforms posses only limited number of orientations, it is not commonly used in the field of defect detection for random texture images. Detection of defects in random textured images requires multi-resolution decomposition of inspected image across several scales. Gabor filters can decompose an image into multiple orientations and scales. The impressive property of Gabor filters which allows optimal localization both in the spatial domain and in the spatial-frequency domain make it one of the most widely used approaches utilized for defect detection purpose in random texture images.

Most work on the analysis of random textured tiles for defect detection is done using Wavelet transform, Gabor filters and other methods [12], [13], [14], [15], [16]. The main drawback that characterizes these approaches is there computational complexity. This paper thus find solution to the problem of real-time automatic defect detection and segmentation for textured tiles by employed multi-scale and multi-orientation Gabor filters along with Self Organizing Map (SOM). The proposed method has comparable improved performance at much faster speed than the existing methods.

The paper is organized as follows: Section 2 and 3 gives a brief review of 2-D Gabor filter and SOM respectively while the proposed method is discussed in Section 4. The simulation results with different images are presented in Section 5 to demonstrate the efficiency of the proposed algorithm. Finally, concluding remarks are given in Section 6.

2. Feature Extraction by Gabor filter

Gabor filters are efficient for extracting texture features based on localized spatial frequency information, which are useful for further analysis such as edge detection and segmentation [17], [18]. The 1-D Gabor function was first defined by Gabor [19], and later extended to 2-D by Daugman [20], [21]. A 2-D Gabor filter is an oriented

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complex sinusoidal grating modulated by a 2-D Gaussian function, which is given by [18], [21], [22], [23]:

$$h_{\sigma,\omega,\theta}(x,y) = g_{\sigma}(x,y)\cdot \exp[2\pi j\omega\,(x\cos\theta + y\sin\theta)] \tag{1}$$

where

$$g_{\sigma}(x,y) = \frac{1}{2\pi\sigma^2}\exp[-(x^2+y^2)/2\sigma^2], \text{ and } j=\sqrt{-1} \tag{2}$$

is the Gaussian function (symmetric or asymmetric depending on the application) with scale parameter σ. The parameters of a Gabor filter are, therefore, given by the frequency ω, the orientation θ and the scale σ.

The Gabor filter $h_{\sigma,\omega,\theta}(x,y)$ forms a complex valued function. Decomposing it into real and imaginary parts gives

$$h_{\sigma,\omega,\theta}(x,y) = R_{\sigma,\omega,\theta}(x,y) + jI_{\sigma,\omega,\theta}(x,y) \tag{3}$$

where

$$R_{\sigma,\omega,\theta}(x,y) = g_{\sigma}(x,y)\cdot\cos[2\pi\omega\,(x\cos\theta + y\sin\theta)]$$

$$I_{\sigma,\omega,\theta}(x,y) = g_{\sigma}(x,y)\cdot\sin[2\pi\omega\,(x\cos\theta + y\sin\theta)]$$

Gabor filters correspond to any linear filters, thus the most straightforward technique to perform the filtering operation is via the convolution in the spatial domain. The Gabor-filtered output of a gray-level image $f(x,y)$ is obtained by the convolution of the image with the Gabor filter $h_{\sigma,\omega,\theta}(u,v)$, i.e.

$$\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} f(x+u, y+v)\bullet h_{\sigma,\omega,\theta}(u,v)\,du dv \tag{4}$$

Given a neighborhood window of size $k\times k$ with $k=2n+1$, the discrete convolutions of $f(x,y)$ with respective real and imaginary components of $h_{\sigma,\omega,\theta}(x,y)$ are

$$h_R(x,y) = \sum_{l=-n}^{n}\sum_{m=-n}^{n} f(x+l, y+m)\bullet R_{\sigma,\omega,\theta}(l,m) \tag{5a}$$

and

$$h_I(x,y) = \sum_{l=-n}^{n}\sum_{m=-n}^{n} f(x+l, y+m)\bullet I_{\sigma,\omega,\theta}(l,m) \tag{5b}$$

Energy $E(x,y)$ at (x,y) within the window $k\times k$ at a specific frequency and at a specific orientation or direction is then written as

$$E(x,y) = h_R^2(x,y) + h_I^2(x,y) \tag{6}$$

This captures the local features which are utilized for texture analysis purposes. An appropriate filter design with small convolution masks allows an efficient implementation of the Gabor filters in the spatial domain [24].

3 Self-Organizing Map

The Self-Organizing Map (SOM) algorithm proposed by Kohonen [25],[26] is a neural network model of the unsupervised class. SOM is used to visualize and interpret large high-dimensional data sets by projecting them to a low dimensional output space, called a feature map, in such a way that topological-ordered relations are preserved [27], [28].

Basically, Kohonen's SOM neural network consists of two layers [28]: the input buffer layer and a Kohonen layer consisting of L cells (neurons). Cells in Kohonen layer are typically located on a regular low-dimensional grid, usually 1- or 2-dimensional lattice. Let $\mathbf{x} = [x_1, x_2, \cdots, x_n]$ be input vectors, and the weight of output layer j be represented by $\mathbf{w}_j = [w_{j1}, w_{j2}, \cdots, w_{jn}]$. When an input $\mathbf{x}$ is presented to the network, the best matching unit (winning unit) is determined by

$$\boldsymbol{b}(\mathbf{x}) = \arg\min_{j} \left\| \mathbf{x} - \mathbf{w}_j \right\|, \quad j = 1, 2, \cdots, N \tag{7}$$

where $\boldsymbol{b}(\mathbf{x})$ represents the index of the winning unit for the input X and $\|\bullet\|$ denotes the Euclidean norm.

The weights are updated as follows, once the winning unit and its topological neighbors are determined

$$\mathbf{w}_j(t+1) = \begin{cases} \alpha(t)[\mathbf{x} - \mathbf{w}_j(t)] & \text{if } j \in N_{b(\mathbf{x})}(t) \\ \mathbf{w}_j(t) & \text{otherwise} \end{cases} \tag{8}$$

where $\alpha(t)$ is the learning rate at time t and $N_{b(\mathbf{x})}(t)$ denote the neighborhood of the winning unit $\boldsymbol{b}(\mathbf{x})$. By this learning rule, the weight vector $\mathbf{w}_j$ of the winning unit $\boldsymbol{b}(\mathbf{x})$ moved towards the input vector $\mathbf{x}$ in the input space, and the topological ordering property emerges from this process.

4. Defect Detection Technique

The proposed technique to detect defects in textured tile images commences by convolving the inspected sample image $f(x,y)$ with each Gabor filter $h_{\sigma,\omega,\theta}(x,y)$ to obtain the output

$$I(x,y) = \left| f(x,y) * h_F(x) \right| \tag{9}$$

With four scales factor and image filtered in orthogonal direction, thus 16-dimensional vectors $\boldsymbol{I}(x,y)$ are obtained

$$\boldsymbol{I}(x,y) = [I_1(x,y), \cdots, I_{16}(x,y)] \tag{10}$$

Every pixel from the acquired image is characterized by a feature vector. A simplified characterization of texture based on relations between the pixels in restricted neighborhood is used. The gray-level values of neighboring pixels form the feature vector for every pixel. The feature vector does not pretend to provide an exhaustive characterization of texture, but they do implicitly capture certain local textural properties such as coarseness, directionality, regularity, etc.

The large dimension of feature vectors generates computational and over-fitting problems. Now we are faced with two conflicting goals. On one hand, it is desirable to simplify the problem by reducing the dimension of feature vectors. On the other hand, the original information content has to be preserved as much as possible. The Kohonen's Self-Organizing Maps (SOM) offers a convenient way to control the tradeoff between simplifying the problem and loosing the information, and is used over the vectors $\{\boldsymbol{I}(x,y)\}$ to generate a 1-dimensional feature map Γ. For each pixel (x,y), the scalar index $P(x,y)$ of the reference vector closest to $\{\boldsymbol{I}(x,y)\}$ is assigned

$$P(x,y) = \arg\min_{i} \left\| \boldsymbol{I}(x,y) - \mathbf{w}_j \right\| \text{ for all } w_j \in \Gamma \tag{11}$$

For each $P(x,y)$, eight sets of neighbors are defined as shown in Fig. 1 [18]. The neighbors from the l direction are arranged as a vector $[P_1^l, \cdots, P_k^l]$, $P_k^l \in N_{xy}^l$. To predict the center value $P(x,y)$ from the neighbors, multilayer perceptrons are trained with the relations,

$$P(x,y) = f^l\left(P_1^l, \cdots, P_k^l\right) + e^l \quad l = 1, \cdots, 8 \tag{12}$$

The absolute error of prediction between $P(x,y)$ and its neighbors N_{xy}^l and sample variance of the prediction errors are computed

$$e^l(x,y) = P(x,y) - f^l\left(P_1^l, \cdots, P_k^l\right) \tag{13}$$

$$\upsilon^2(x,y) = \frac{\sum_{l=1}^{8}(e^l(x,y) - \mu(x,y))^2}{8} \tag{14}$$

where $\mu(x,y)$ is the mean of $(e^l(x,y))_{l=1}^{8}$.

The Gaussian smoothing is performed on sample variance to remove local fluctuation effect.

$$\boldsymbol{U}(x,y) = G_\sigma(x,y) * \upsilon^2(x,y) \tag{15}$$

where, $G_\sigma(x,y)$ denotes Gaussian filter and $\boldsymbol{U}$ denotes a smoothed variance image.

Canny's edge-detection method is applied to the variance image $\boldsymbol{U}$. The Canny operator works in a multi-stage process. First of all the image is smoothed by Gaussian convolution

$$\boldsymbol{K}(x,y) = G_\sigma(x,y) * \boldsymbol{U}(x,y) \tag{16}$$

where

$$G_\sigma = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left[\frac{-x^2 + y^2}{2\sigma^2}\right] \tag{17}$$

Then gradient of $\boldsymbol{K}(x,y)$ is computed using Sobel operator

$$\boldsymbol{M}(x,y) = \sqrt{K_x^2(x,y) + K_y^2(x,y)} \tag{18}$$

and

$$\theta(x,y) = \tan^{-1}\left[K_y(x,y) / K_x(x,y)\right] \tag{19}$$

Edge map is produced by thresholding the gradient magnitude

$$E_\tau = \begin{cases} M(x,y) & \text{if } M(x,y) \ge \tau \\ 0 & \text{Otherwise} \end{cases} \tag{20}$$

5. Simulation Results

In this section, the simulation results from the test database consisting of 150 textured tiles images with 256×256 pixels (8 bit grey level range) are presented. Database images consist of 130 defective tiles in addition with 20 perfect tiles. The tiles used in our experiments were ceramic, granite, and marble of a size of at least 200×200 mm. The experiment is conducted using process described in Sect. 3. In the implementation, the tile images are decomposed using Gabor wavelets with the following parameters, frequency bandwidth ($\omega = 1.5$), four scale factors ($\sigma = 1.5, 2, 2.5$, and 3), and four orientation angles ($\theta = 0^\circ, 45^\circ, 90^\circ$, and 135°). The feature vectors for training are extracted from a small image pitch of typically 65×65 pixels in the region of image having defect and in the region of defect free image respectively. The dimensions of feature vectors are substantially reduced with the SOM. The SOM used for projecting the data nonlinearly onto a lower-dimensional display consists of 16 input nodes in the input layer and a 10x10 array of nodes in the output layer. The resulting training vectors are smoothed by using a Gaussian filtering mask with $\sigma = 6.5$ to reduce noise in the output image. Considering both the computational effort involved and the filtering quality, in the proposed scheme, the sizes of the masks created from the Gaussian smoothing filter and the optimal imaginary Gabor filter are both set to 7×7. Final edge map of the image is obtained after applying Canny's edge detector with threshold value of 0.95.

The developed defect detection technique is run on Pentium 450 MHz PC using a simple C program. The performance of the proposed technique is determined by visually assessing the binary output images. Figure 2 and 3 shows some of the corresponding segmentation results. The proposed scheme achieved a promising level of accuracy and robustness in textured tiles defect detection and can successfully segment the defects with different shapes, different positions and different texture backgrounds.

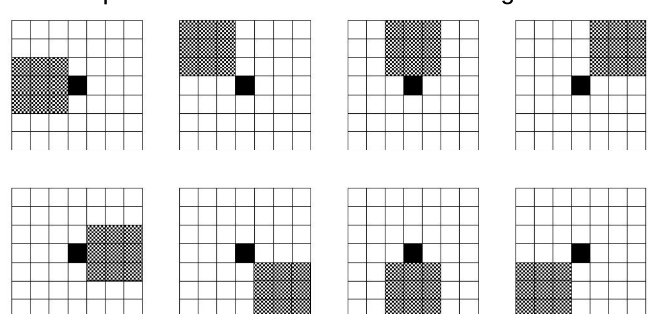

Figure 1: Eight sets of neighbors

6. Conclusions

In this paper, a novel defect detection and segmentation scheme for textured tiles has been proposed. The technique combines concepts of multi-scale and multi-orientation

Gabor filters along with SOM to locate the local surface defects on various textured tiles. In the proposed technique, Gabor filter parameters, such as, frequency bandwidth, the upper and lower center frequencies are chosen based on neurological findings, proposed in [6], [29]. The incorporation of feature extraction using SOM improves the performance and also reduces the complexity of the feature extraction and detection stages. A variety of typical defects are detected successfully and the ceramic tile defect segmentation results obtained by this method are found to be satisfactory. By the proposed method, a general improvement in the area of machine vision is achieved. The success of the proposed technique can be further improved by increasing the number of scales and orientations in Gabor decomposition and by varying the other Gabor filter parameters.

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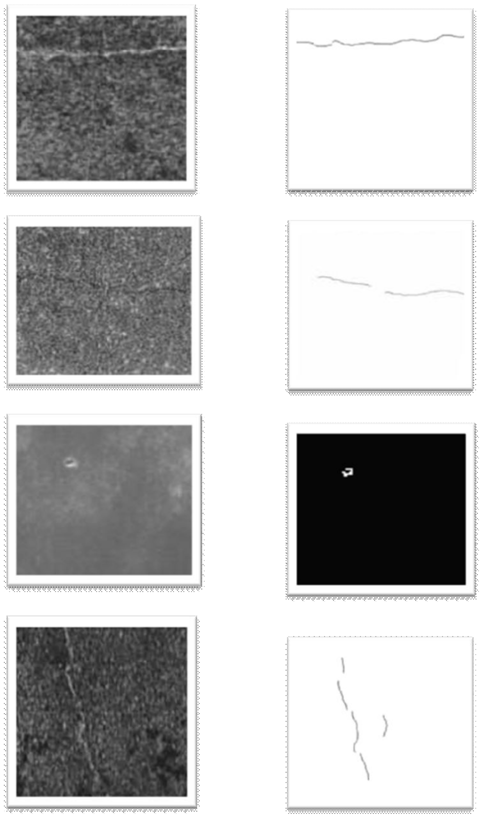
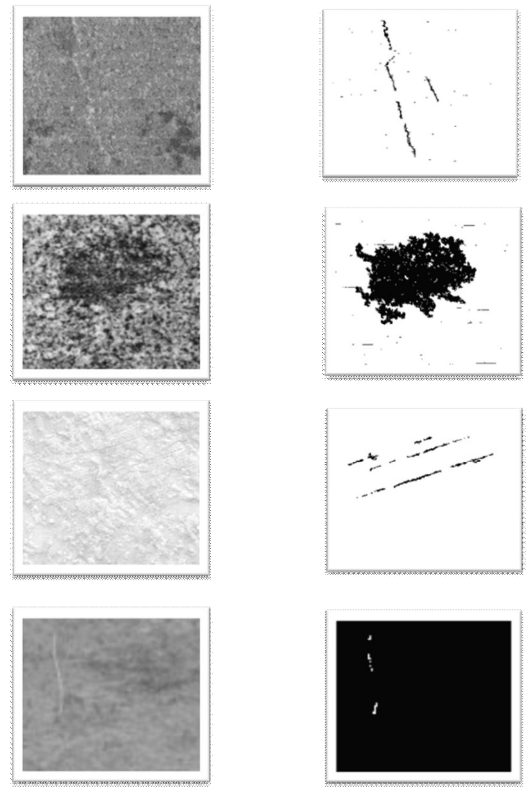


(a) (b)

Figure 3 : (a) Defective Tiles: from top to bottom (b) Final edge map obtained using proposed algorithm on the images in (a).



(a) (b)

Figure 2 : (a) Defective Tiles: from top to bottom (b) Final edge map obtained using proposed algorithm on the images in (a).