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Multi-Resolution and Noise-Resistant Surface Defect Detection Approach Using New Version of Local Binary Patterns

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Abstract: Visual quality inspection systems play an important role in many industrial applications. In this respect, surface defect detection is one of the problems which have been paid much attention on by image processing scientists. Until now different methods have been proposed based on texture analysis. An operation which provides discriminate features for texture analysis is local binary patterns (LBP). LBP first introduced for gray-level images which makes it useless for colorful samples. Sensitivity to noise is another limitation of LBP. In this paper a new noise resistant and multi-resolution version of LBP is used which extracts color and texture features jointly. Then, a robust algorithm is proposed for detecting abnormalities in surfaces. It includes two steps. First new version of LBP is applied on full defect-less surface images and the basic feature vector is calculated. Then, by image windowing and computing the non-similarity amount between windows and basic vector, a threshold is computed. In test phase, defect parts are detected on test samples using the tuned threshold. High detection rate, low computational complexity, low noise sensitivity and rotation invariant are some advantages of our proposed approach.
Keywords: Surface Defect Detection, Local Binary Patterns, Noise Resistant, Multi-Resolution, Logarithm Likelihood Ratio, Texture analysis

1. INTRODUCTION

Any hole, damage, abnormalities and slot in products surfaces are called defect [1]. Defects on product surfaces affect quality of that. The main aim of Visual quality inspection systems (VQIS) is detecting abnormalities in surface images. VQIS can be used in many industrial applications such as tiles, metal, agricultural products, fabric, paper, etc. Until now many different methods have been proposed to do this task. State-of-the-art approaches can be categorized in three categories as: Spatial Domain, Frequency Domain and Joint Domains.

For instance, Henry et al. [2] proposed an approach in [2] based on ellipsoidal region features and min-max technique. It was evaluated on patterned fabrics to detect defect parts automatically. It can be categorized in spatial domain.

Threshold is one of common methods to separate objects from background in VQIS. In [3], an improved extension of Otsu threshold is proposed for surface defect detection. Their proposed approach is Weighting object variance in Unimodal or bimodal histograms of input images. This approach is run in spatial domain. As a recent work, in [4] a texture defect detection system is described based on image deflection compensation. A general surface defect detection method is proposed in [5], which is invariant with respect to texture descriptor. They proposed a one dimensional version of local binary patterns to detect defects on fabric textile and stone surfaces.

Ghazini et al. [6] proposed a defect detection approach of tiles using combination of wavelet transform and statistical features. It is evaluated in frequency domain. In [7] a probabilistic neural network (PNN) is used for fast defect classification based on the maximum posterior probability of the Log-Gabor based statistical features. In [8], authors extracted some wavelet features to identify images. Then a Genetics based algorithm is proposed for fabric defect detection based on shanon entropy. Alimohammadi et al. [9] proposed a new method using optimal Gabor filters to detecting skin defect of fruits which was usable in agricultural products visual quality inspection systems (APVQIS). Some researchers try Fourier transform to achieve this aim. For example, in [10], Chan and Pang proposed a robust approach for fabric textile defect detection by Fourier analysis. They defined a diagram which is called central spatial frequency spectrum to analysis an image. A review paper about defect detection approaches is proposed in [11].

The mathematical/computational complexity of some previous approaches is high and some of them don't guarantee an accurate result for every kind of surfaces. Noise and rotation sensitivity can be mentioned as big limitations of many state-of-the-art approaches. The main aim of this paper is to propose an approach for surface defect detection which satisfies mentioned limitations.

The Local binary patterns (LBP) is a non-parametric operator which describes the local spatial structure and local contrast of an image. Previous researches shows it's power to extract discriminate features to distinguish and identify surfaces.

In this paper first, a noise resistant and multi-resolution version of LBP is proposed which extracts color/texture features jointly. It is called Noise resistant Color Local Binary Patterns (NrCLBP). Next, a novel approach is proposed for detecting surface defects using NrCLBP. The proposed approach detection algorithm includes two phases. In the first phase, some surely defect-less images were taken and analyzed by NrCLBP operator and a

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basic feature vector is extracted, which is a good identification for non-defects parts. Then, by using image windowing technique and Log-Likelihood ratio, an accurate threshold is computed for defect-less image. In the second phase by extracting NrCLBP features of test images and compared them with extracted basic feature vector, defect parts are detected. In the result part, two experiments are evaluated on two different databases which include fabric textile surface and stone surface images. High detection rate in comparison with other state-of-the-art methods shows the quality of the proposed approach. Low computational complexity, rotation invariant, illumination invariant, noise resistant and multi-resolution are some other advantages of the proposed approach.

1.1 Paper organization

The paper is organized as follows: In section2, first, basic theory of local binary patterns (LBP) is discussed as a texture descriptor. Then modified version of LBP is survived. In section 3, our proposed noise resistant and multi-resolution texture analysis operation is described, which extracts color/texture features jointly. Section 4 presents our proposed surface defect detection algorithm. Experimental results are included section 5. Finally, the conclusion is presented in section 6.

2. LOCAL BINARY PATTERNS

Local binary pattern (LBP) was originally proposed in [12] for the first time. LBP is an texture analysis operator which describes the local contrast and local spatial structure of an image. In order to evaluate the LBP, at a given pixel position (x_c , y_c), LBP is described as an ordered set of binary comparisons of pixel intensities between the center pixel and its neighbors. Neighborhoods could be assumed circular because of achieving the rotation invariant. Points which the coordination's are not exactly located at the center of pixel would be found by bilinear interpolation. LBP are defined as follows:

$$\mathbf{LBP_{P,R}} = \sum_{k=1}^{p} \phi(g_k - g_c)2^{k-1} \qquad (1)$$

Where, "g_c" corresponds to the grey value of the centered pixel and "g_k" to the grey values of the neighborhood. P will be the number of neighborhoods, and function $\phi(x)$ is defined as:

$$\boldsymbol{\phi}(\mathbf{x}) = \begin{cases} 1 & \text{if} \quad x \geq 0 \\ 0 & \quad\quad \text{else} \end{cases} \qquad (2)$$

An example of applying $LBP_{8,1}$ operator is shown in Figure1.

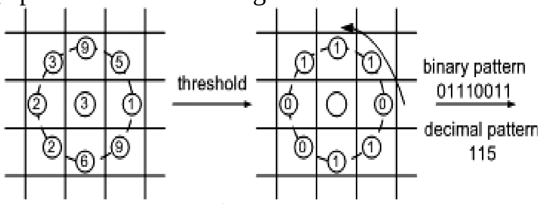

Figure 1. An example of applying LBP with P=8 and R=1

The $LBP_{P,R}$ operator produces (2^P) different output values, corresponding to the 2^P different binary patterns that can be formed by the P pixels in the neighbor set. When the image is rotated, the gray values "g_k" will correspondingly move along the perimeter of the circle around "g_c". To remove the effect of rotation, i.e. to assign a unique identifier to each rotation invariant local binary patterns is defined:

$$\mathbf{LBP_{P,R}^{ri}} = \min\{ROR(LBP_{P,R}, \beta) \mid \beta = 0,1, \dots, p-1\} \qquad (3)$$

Where "ri" means rotation invariant and ROR(x, β) performs a circular bit-wise rotate right on the P-bit number x, β times. Finally, the minimum of computed values for β=0 to p-1 would be choose.

2.1. Modified Local Binary Patterns (MLBP)

Practical experience of the authors in [13] has shown that LBP doesn't provide very good discrimination, and the computation complexity is high. To solve these problems, Ojala, et al.[14] proposed a new version of LBP which is known as modified local binary patterns (MLBP). Ojala et al. [14] defined a uniformity measure "U", which corresponds to the number of spatial transitions (bitwise 0/1 changes) in the "pattern". It is shown in Equation4. For example, pattern 11111111 has U value of 0, while 11001001 have U value of 3.

$$\mathbf{U}(\mathbf{LBP_{P,R}}) = |\phi(g_1 - g_c) - \phi(g_p - g_c)| + \sum_{k=2}^{p} |\phi(g_k - g_c) - \phi(g_{k-1} - g_c)| \qquad (4)$$

Applying MLBP, the patterns which have uniformity amount less than U_T are grouped as uniform patterns and the patterns with uniformity amount more than U_T grouped as non-uniform patterns. Finally, the LBP is computed as follows.

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$$\mathbf{LBP}_{\mathbf{P,R}}^{\mathbf{riu_T}} = \begin{cases} \sum_{k=1}^{P} \phi(g_k - g_c) & \text{if } U(LBP_{P,R}) \leq U_T \\ P+1 & \text{elsewhere} \end{cases} \qquad (5)$$

"riu_T" reflects the use of uniform threshold. Applying $LBP_{P,R}^{riu_T}$ will assign a label from *0* to *P* to uniform patterns and label *P+1* to non-uniform patterns. In using $LBP_{P,R}^{riu_T}$ just one label *(P+1)* is assigned to all of the non-uniform patterns. To achieve discriminative features, U_T should be optimized that uniform labels cover majority patterns in the image. Recent researches [1, 5, 15, 16] show that if the value of U_T is selected equal to (P/4), only a negligible portion of the patterns in the texture takes label P+1. $LBP_{P,R}^{riu_T}$ quantifies the occurrence statistics of individual rotation invariant patterns corresponding to certain micro-features in the image, hence the patterns can be considered as feature detectors. For example, Figure 2, illustrates the 36 unique rotation invariant local binary patterns that can be occurred in the case of P=8 and R=1. For example, pattern #0 detects bright spots, #8 dark spots or flat areas, #4 edges, etc.

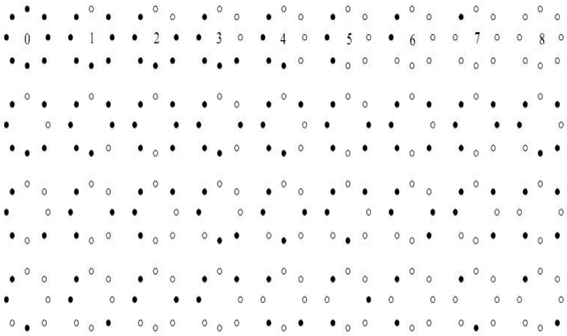

Figure2. The 36 unique rotation invariant binary patterns that can occur in the circularly symmetric neighbor set of $LBP_{8,R}$. Black and white circles correspond to bit values of 0 and 1 in the output
(a) Hatchet Stone (b) Orange Travertine Stone (c) Creamy Travertine Stone
(d) Box Pattern Fabric (e) Star Pattern Fabric (f) Dot Pattern Fabric

One label is assigned to each neighborhood. So, a feature vector like *D* can be extracted for each image as follows:

$$D = < d_0, d_1, ..., d_{P+1} > \qquad (6)$$

Where:

$$d_k = \frac{N_k}{N_{total}} \qquad 0 \leq k \leq P+1 \qquad (7)$$

N_k shows total number of neighbors that labeled as *K*, and N_{total} is the size of input image. finally, extracted vector have *P+2* dimensions. Where, d_k is the occurrence probability of label *k* in whole. To obtain d_k, first $LBP_{P,R}^{riu_T}$ should be applied on the whole image and the labels are assigned to neighbors. Then the occurrence probability of each label in the image is regarded as one of the dimensions of the feature vector.

3. NOISE RESISTANT COLOR LBP (NrCLBP)

The basic LBP scheme and most of it's improved versions such as MLBP [14], MBP [18], LTP [20] were defined for grayscale images. We propose a simple extension to color images. The proposed descriptor is invariant with respect to several transformations in the color spaces. Color images can be represented in different color spaces such as RGB, HSV, YC_bC_r, etc. In this part, the definition is evaluated in RGB. RGB uses an additive color mixing model of red, green and blue colors. To represent color images, separate red, green and blue components must be specified for each pixel and so the pixel value is actually a vector of three numbers, which are known as g_r, g_g, g_b. Often the three different components are stored as three separate `grayscale' images known as *color planes* which have to be recombined when processing.
In order to combine color and texture information, each colorful input texture can be separated in three different color spaces. Now, the proposed texture analysis operator (Equation 6) can be computed for each color plans separately. Finally, the extracted vectors can be concatenated in a simple representation as follows:

$$D = < D_R, D_G, D_B > \qquad (8)$$

Where, D_R shows the extracted feature vector for color plane red using Equation 6. Also, D_G and D_B can be defined in a similar ways. Finally, vector D has 3P+6 dimensions.

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3.1. Noise Resistant

Image noise is random variation of brightness or color information in images, and is usually an aspect of electronic noise. Noise produces undesirable effects such as artifacts, unrealistic edges, unseen lines, corners, blurred objects and disturbs background. In this respect, different noise models can be defined such as Gaussian, white, Browning, impulse valued, periodic, quantization, etc. Impulse noise is seen in data transmission. Some image pixel values are replaced by corrupted pixel values. Impulse Noise sensitivity is one of the big limitations of the LBP, which decreases the analysis accuracy. Even a small noise may change the LBP code significantly. In the evaluation of $LBP_{P,R}^{riu_T}$, threshold is considered at exactly the value of the central pixel, so LBP tends to be sensitive to noise, especially in near uniform image regions. It causes change label of the desired centered pixel which effects on final extracted feature vector. For example, suppose two different local neighbors as it is shown in Figure 3.a and Figure 3.b.

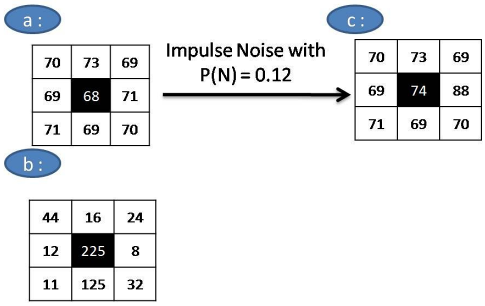

Figure3. Noise effects on MLBP

An impulse noise is applied on Figure3.a, and output is shown in Figure 3.c. The extracted labels for each pattern are as follows:

$$LBP_{8,1}(a)=8 \quad LBP_{8,1}(b)=0 \quad LBP_{8,1}(c)=0$$

The Figure 3.a shows a local flat area, and Figure3.b shows a local bright spot. As a human visual inspection result, the Figure 3.c shows flat area and it is more similar to the Figure 3.a, but it's LBP label is same with Figure 3.b. In this section, we propose an impulse noise resistant version of LBP. The texture analysis techniques discussed above (Basic LBP, MLBP) had been defined for grayscale images. We proposed a simple extension of this technique to color images in previous section. In a gray-level image like G, impulse noise can be defined as transmission function like N that probability changes some of the image pixel values as follows. Where G' shows the output noisy image.

$$G(x,y) \pm N(x,y) = G'(x,y) \qquad (9)$$

The noise occurrence probability on a specific pixel at given position (x,y), can be considered as P(N). In a colorful image with "i" color planes, at a given pixel position (x , y), impulse noise can be defined as follows:

$$G(x,y,i) \pm N(x,y,i) = G'(x,y,i) \qquad (10)$$

In a colorful image, noise can be fall in one or more color planes. It means noise may be fall on a pixel in a specific plane with probability of P(N)/3. So, the probability of occurring noise on all channels of a specific pixel contemporary is $(P(N))^{3}$, which is very low. It means that pixel values of a given pixel at position (x, y) may not change at least in one of the color planes. To assume this mention, function Ω(x) can be new defined as follows:

$$\Omega_X = \begin{cases} 1 & if\ (\Omega_{X_R} \times \Omega_{X_G} \times \Omega_{X_B}) = 1 \\ 0 & if\ (\Omega_{X_R} \times \Omega_{X_G} \times \Omega_{X_B}) = 0 \end{cases} \qquad (11)$$

Where

$$\Omega_{X_i} = \begin{cases} 1 & if \quad (f'_{i_k} - f'_{i_c}) > 0 \\ 0 & else \end{cases} \qquad (12)$$

Where, G'_{i_c} corresponds to the grey value of the center pixel in color plane *i* (e.g. R, G, and B) in noisy image. G'_{i_k} shows the grey values of the neighborhoods in the same color plane *i* in noisy texture image. In this respect, an unlike noise on centered pixel or its neighbors in one or two channels, can't change the final pattern and extracted label. In other words, a neighbor pattern can be desired as 1, just when it's intensity value is more than threshold (center value) in all of the color planes. In this respect, a new LBP representation can be defined for color textures with notation $NrCLBP_{P,R}$ as abbreviation of Noise resistant Color Local binary patterns. For a colorful image in RGB, along with three previous extracted vectors, new feature vector can be extracted using $NrCLBP_{P,R}$. Finally, extracted vectors can be concatenated in a single representation as follows:

$$D = < D_H, D_R, D_G, D_B> \qquad (13)$$

Where, D_H shows the extracted feature vector based on $NrCLBP_{P,R}$.

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4. PROPOSED SURFACE DEFECT DETECTION APPROACH

Any hole, damage, and abnormalities in surfaces are called defect. In this section, an approach is proposed for detecting defects in surfaces. The proposed approach has general theory which is invariant with respect to texture descriptor type. It consists training phase and test phase.

4.1. Train Phase

In this phase, first an image is taken from the surface which is defect-less. Then texture analysis operator is applied over the whole image. In this paper, NrCLBP is used as color/texture analysis operation. Then, regarding the Equation13 one feature vector is extracted. This vector is called "Basic feature vector" and is marked by M.

Then the defect-less image is divided into windows of sizes W×W pixels. After that, the NrCLBP is applied over each of these windows. Thus, for each window, a feature vector is extracted. Next, non-similarity amount of windows vector is computed through the basic feature vector (M) based on Log-likelihood ratios as follows:

$$\mathbf{L_i} = (S_i, M) = \sum_{k=1}^{L+1} S_{ki} \log\left(\frac{S_{ki}}{M_k}\right) \quad i = 1,2,\ldots,N \qquad (14)$$

Where "S_i" is the feature vectors which was extracted for "i_{th}" window. M shows the basic feature vector. Also, N is the total number of windows and "k" represents the "K_{th}" dimension of the feature vector.

Since minimization of Log-likelihood ratio shows the similarity to specific class. So, the maximum value among these ratios is regarded as the threshold for the defect-less window. (Equation15)

$$\mathbf{T} = \max(L_i) \quad i = 1,2,\ldots,N \qquad (15)$$

Where, T is known as the defect-less threshold. "L_i" shows the non-similarity amount between "i_{th}" window and Basic vector (M).

4.2. Test Phase

First, the test image is divided into windows of size W×W pixel. Then, for each window, the feature vector is extracted using NrCLBP. After that, for each of these windows the log-likelihood ratio is computed as follows:

$$\mathbf{D_i} = (R_i, M) = \sum_{k=1}^{L+1} R_{ki} \log\left(\frac{R_{ki}}{M_k}\right) \quad i = 1,2,\ldots,N \quad (16)$$

Where "R_i" is the feature vector which is computed for "i_{th}" window of test image. M is the basic vector. Also, N shows the total number of windows and "k" represents the "k_{th}" dimension of the feature vector. After computing non-similarity ratio between test window vectors and basic vector, for each window, if any of these ratios is greater than the corresponding threshold, the window is declared as the defected window. It is shown in Equation17.

$$\mathbf{i_{th}\ Window} = \begin{cases} \mathbf{Defected} & \text{if } D_i > T \\ \mathbf{Non-Defected} & \text{otherwise} \end{cases} \quad (17)$$

Output of the proposed approach is called "defect pattern" which is a binary image. Black pixels in the defect pattern represent defect-less areas of the surface and white pixels represent defected areas.

4.3. Multi Resolution Analysis

The proposed approach is a multi resolution method. So, the results of choosing the different size of Neighborhood radius (R) in $NrCLBP_{P,R}$ can be mixed by using the following equations, and it can be used for detecting the abnormalities in the surfaces. It is shown in the following equation:

$$L_i^Z = \sum_{z=1}^{Z} L_i(R_i^z, M_z) \qquad (18)$$

Where, Z is the number of $NrCLBP_{P,R}$ different sizes and "i" corresponds to the "i_{th}" windows.

5. EXPERIMENTAL RESULTS

In this paper, a general surface defect detection approach and a noise resistant color/texture descriptor were proposed. To evaluate the effectiveness of our proposed approach, we carried out experiments on two surface datasets: architectonic stone [1, 16] and Fabric Textile [15, 17].

The architectonic stone database [1] contains 60 images in 3 categories known as "Non-Wavy Creamy Travertine", "Hatchet" and "Orange Travertine". Each category consists 20 images were taken by a digital camera with resolution of 0.2 mm/pixel. Images are in different sizes that are collected under different illuminations and angles. The Patterned Fabric database [15] contains 3 categories of patterned fabric textiles

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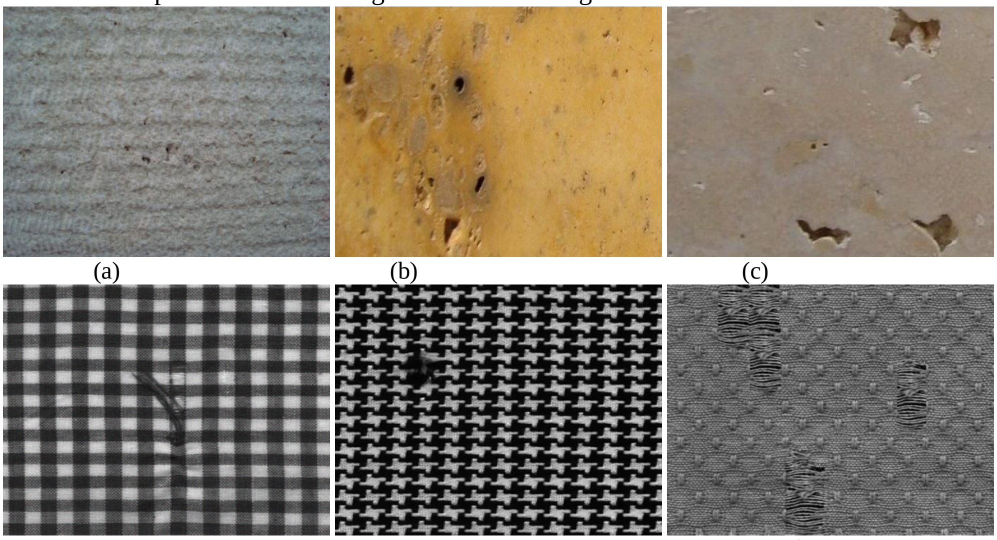
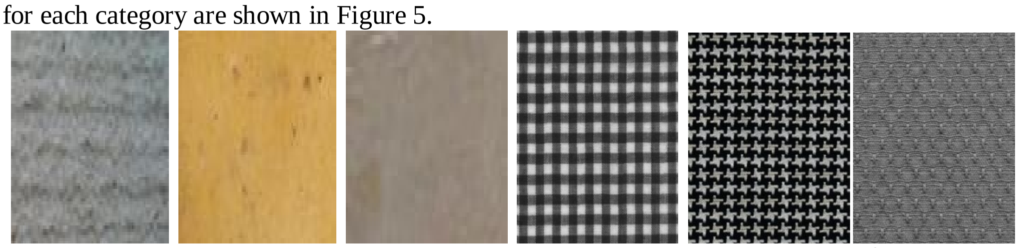
called "Dot- Pattern", "Star- Pattern" and "Box- Pattern". It was provided by Department of electronic and electric of Hong-Kong University. We selected randomly 20 images from each category to evaluate the experiment. Some examples of database images are shown in Figure 4.



(a) (b) (c) (d) (e) (f)

Figure 4. Some examples of database images

First of all, one fully defect-less image of each category in size of 64×64 was provided for train phase. Train samples for each category are shown in Figure 5.



(a) (b) (c) (d) (e) (f)

Figure 5. Train Defect-less samples (a) Hatchet Stone (b) Orange Travertine (c) Non-Wavy Creamy Travertine (d) Box-Pattern Fabric (e) Star-Pattern Fabric (f) Dot-Pattern Fabric

Next the proposed approach based on different radius (R) and neighbors (P) of $NrCLBP_{P,R}$ was applied on database. One binary output defect pattern was provided for each test image. In order to evaluate performance, detection rate was used as follows. Detection rate is one of the popular criteria for measuring the performance of surface defect detection approaches [1, 5, 15, 16, 17].

$$\boldsymbol{Detection\ Rate} = 100 \times \frac{N_{RND} + N_{RD}}{N_{total}} \quad (19)$$

To measuring the detection rate, the binary output defect pattern was divided to non-overlap windows by the sizes of W×W pixels which is called "part" in this paper. After that, each part that has at least one defected pixel was counted as a defected part. Different sizes were tested for windowing, finally size 16×16 was provided maximum detection rate in both of experiments.

In Equation21, N_{RD} means the total number of parts that were really defected and also were detected as defect part. N_{RND} means the number of parts which were really defect-less and also were detected as defect-less part. For example, in Figure6 an output binary defect pattern is shown where the first window (first column and first row) is categorized as non-defected part and the fourth window (fourth column and first row) is categorized as defected part.

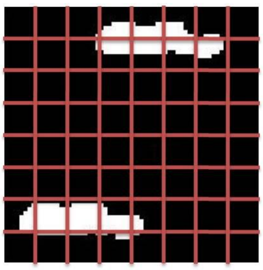


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Figure 6. Determining result by defect detected image

Detection accuracy results on stone database are shown in table 1. Detection accuracy results on patterned fabric textile database are shown in table 2. In order to evaluate performance accurately, specificity and sensitivity were computed for all of the defect patterns (Table 3).

$$\textbf{Specificity} = \frac{TN}{TN+FP} \quad (20) \qquad \textbf{Sensitivity} = \frac{TP}{TP+FN} \quad (21)$$

Where, TP, TN, FP and FN means true positive, true negative, false positive and false negative.

Table1. The average of detection rate of applying multi-resolution LBP with different P and R, on stone database

Features	Category / Operation	Creamy Travertine	Hatchet	Orange Travertine
10	$NrCLBP_{8,1}$	93.47	92.24	90.33
18	$NrCLBP_{16,2}$	**96.2**	95.85	**95.90**
26	$NrCLBP_{24,3}$	90.42	91.39	95.82
10 + 18	$NrCLBP_{8,1} + NrCLBP_{16,2}$	93.60	94.47	93.71
10 + 26	$NrCLBP_{8,1} + NrCLBP_{24,3}$	92.37	95.70	92.64
18 + 26	$NrCLBP_{16,2} + NrCLBP_{24,3}$	90.53	**97.8**	93.15
10 + 18 + 26	$NrCLBP_{8,1} + NrCLBP_{16,2} + NrCLBP_{24,3}$	89.62	90.17	91.14

Table2. The average of detection rate of applying multi-resolution LBP with different P & R on fabric textile database

Features	Category / Operation	Dot Pattern	Box Pattern	Star Pattern
10	$NrCLBP_{8,1}$	95.32	96.57	95.84
18	$NrCLBP_{16,2}$	96.18	**98.1**	**97.5**
26	$NrCLBP_{24,3}$	92.16	93.77	92.90
10 + 18	$NrCLBP_{8,1} + NrCLBP_{16,2}$	**97.5**	94.50	95.66
10 + 26	$NrCLBP_{8,1} + NrCLBP_{24,3}$	92.37	90.72	94.38
18 + 26	$NrCLBP_{16,2} + NrCLBP_{24,3}$	91.85	92.26	93.28
10 + 18 + 26	$NrCLBP_{8,1} + NrCLBP_{16,2} + NrCLBP_{24,3}$	90.18	90.37	91.06

Table3. Specificity and Sensitivity of applying proposed approach on two databases

Dataset	Architectonic Stone			Patterned Fabric		
Category Criteria	Creamy Travertine	Hatchet	Orange Travertine	Dot Pattern	Box Pattern	Star Pattern
Sensitivity	93.4	95.1	94.1	93.7	94.2	96.4
Specificity	96.7	96.9	96.8	98.1	98	97.7

5.1. Comparison with State-of-the-art

In order to compare effectiveness of our proposed NrCLBP, some efficient versions of LBP were evaluated as follows:

MBP was introduced in [18]. In MBP the median gray value of the neighborhood is used instead of center pixel threshold using the following definition:

$$MBP_{N,R}(x,y) = \sum_{k=0}^{P-1} \Omega(f_k - f_{median})2^k + \Omega(f_c - f_{median})2^P \qquad (22)$$

Where:

$$f_{median} = Median(\{f_0, f_1, \ldots, f_{P-1}, f_c\}) \qquad (23)$$

It provides local variance information along with local spatial structure together. Some overhead computation and noise sensitivity are disadvantages of MBP.

In the basic LBP and MLBP operator, selecting neighborhood in circular form is to make the algorithm invariant to rotation. Since during some applications, selecting circular neighborhood is not necessary. Also, computing brightness using interpolation in circular neighborhood needs a large amount of computations. Therefore, in 1DLBP [1, 5], the neighborhood is a row (column) wise line segment. In order to apply 1DLBP, the gray value of the first pixel in the segment is compared with gray value of other pixels in the segment. In this version of LBP, the uniformity measure "*U*" corresponds to the number of spatial transitions (bitwise 0/1 changes) in the

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row (column) segment. The method of [19] uses Bollinger bands for detecting defects in patterned fabrics. Bollinger bands consist of three bands: upper, middle, and lower. In this method, patterned fabrics can be considered as comprising many rows (columns), with a pattern designed on each row (column). The principle of this method is that the patterned rows (columns) will generate periodic upper and lower bands. Any defect region in patterned fabric means that there would be a break of periodicity in the pattern. Also, MLBP as it was described in section 2.1 is applied on two databases. We used reported result in [1] on stone database using 1DLBP. Also, the reported result in [5] on patterned fabric textile database using 1DLBP is shown in table 4. Result in [15] on fabric textile database using MLBP and Bollinger bands are used in table 4. The standard proposed MBP in [18] is evaluated by us on two databases. In all experiments, the number of test set samples is same, 20 images in each category. Also, one really non-defected image was used as train set input.

Table 4. Comparison detection rate results (%) of state-of-the-art approaches on two datasets.

Dataset	**Architecture Stone**			**Patterned Fabric Textile**		
Category Operation	Creamy Travertine	Hatchet	Orange Travertine	Dot Pattern	Box Pattern	Star Pattern
Proposed NrCLBP	**96.2**	**97.3**	**95.90**	**97.2**	**98.1**	**97.5**
MLBP [15]	93.67	94.11	95.43	96.5	97.6	97.4
$1DLBP_8$ [1, 5]	95.60	96.22	95.74	96.6	97.8	96.8
MBP [18]	92.36	90.17	91.25	94.31	92	92.8
Bollinger Bands [19]	--	--	--	95.1	94.8	94.6

As it is shown in table 4, the proposed approach provides higher detection rate in comparison with previous versions of LBP and some state-of-the-art approaches on two database. Some examples of output binary defect patterns are shown in Figure 7.

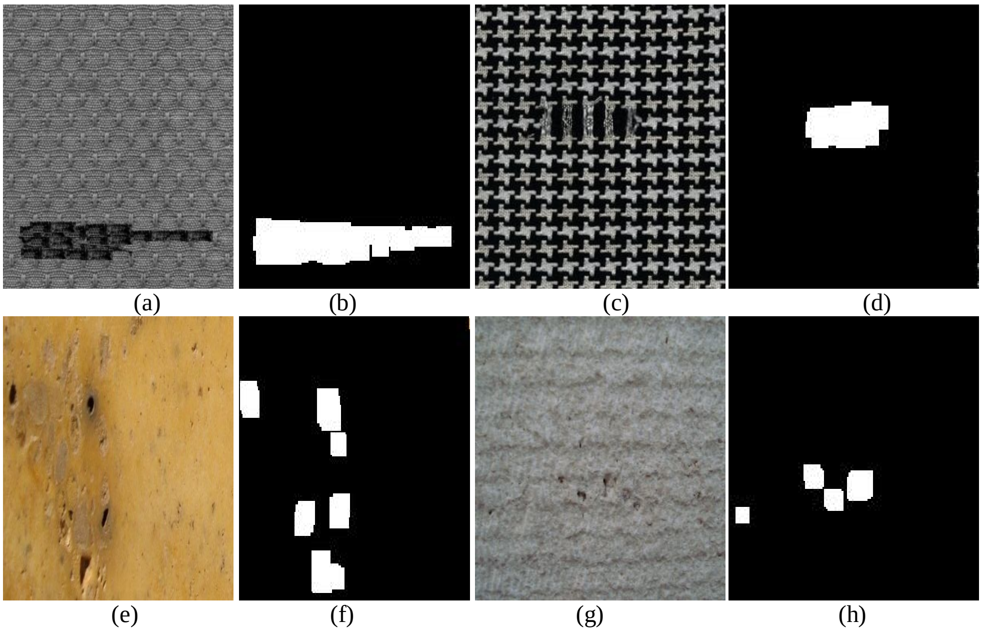

Figure 7. (a) Original Image of Dot-pattern Fabric (b) defect Pattern of (a) by $NrCLBP_{8,1} + NrCLBP_{16,2}$
(c) Original Image of Star-Pattern Fabric (d) defect Pattern of (c) by $NrCLBP_{16,2}$
(e) Original Image of Orange Travertine (f) defect Pattern of (e) by $NrCLBP_{16,2}$
(g) Original Image of Hatchet stone (h) defect Pattern of (g) by $NrCLBP_{16,2} + NrCLBP_{24,3}$

6. CONCLUSION

In this paper a color/texture descriptor as a new version of LBP was proposed which is impulse noise resistant, multi-resolution and rotation invariant. Then, a general surface defect detection algorithm was proposed which was invariant in respect of texture descriptor. Finally, proposed detection algorithm was evaluated using proposed NrCLBP. The experimental results have showed that the proposed approach has a high detection rate for much kind of surfaces. Some other advantages of this approach are as follows:

I) Noise resistant, because of considering color plane information jointly.

II) Low computational complexity, because the base theory of proposed operation is approximately same to MLBP. Just one stage, AND logical combination, is added. This advantage make our proposed approach use-full in online applications

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III) Generality and Usability, the proposed descriptor NrCLBP is a general color/texture descriptor which can be used in many image processing applications

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