Porosity detection by using Improved Local Binary Patterns

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Abstract: - Texture defect detection became one of the problems which has been paid much attention on by image processing scientists since late 90s. Since now many different methods have been proposed to analysis and classification textures. An approach which provides good features to classification is local binary patterns. In this paper an approach is proposed to detection porosity in stones by using the improved form of local binary patterns features. The proposed approach includes two stages. First of all, in train stage, by applying local binary pattern operator on absolutely porosity less images, the basic feature vector is calculated. After that, by image windowing and computing the non-similarity amount between these and basic vector, the porosity-less threshold is computed. Finally, in test stage, by using the porosity-less threshold the porosities is detected on test images. In the result part, the accuracy rate of proposed approach is computed by applying on some captured images and compared with some previous methods. High detection rate, low time complexity, rotate invariant and noise insensitive are advantages of proposed approach. Also, the proposed approach can use for every case of defect detections or visual classification.

Keywords: -Defect Detection, Feature extraction, Porosity, Local Binary Pattern, Visual Inspection

1 Introduction

Any hole, damage and slot in stone are called porosity. The porosity amount is too important for architectonic stones. Because, the quality of structure is depended to this. Also, the strength of structure or building against earthquake and torrent is depended to porosity amount. The porosity amount is computed by equation (1).

\[ \text{Porosity Amount} = \frac{\text{P.A(m}^2\text{)}}{\text{S.A(m}^2\text{)}} \times 100 \]  (1)

Where, P.A means the porosity area which computed in Meter Square measure and S.A is full stone area that computed in same measure. So porosity amount is percental. Some examples of porosity are shown in fig (1).

Now, in near all of stonecutting factories, the porosity amount computes by human. So, it’s necessary to propose a visual inspection approach to decrease time and money complexities and increase detection accuracy rate. According to stone images, the porosity is categorized as defect. So, the proposed approach should be a visual defect detection algorithm which names visual inspection algorithm.

Consequently, since now, many different approaches are proposed for defect detection for different cases. For example, Zhaoa and Yeb [1] are proposed an approach for wood defect detection recognition. In [2] the authors offered an accurate method for ceramic tiles visual inspection system. In [3], [4] and [5] some defect detection approaches are proposed for cases such as leather, fabric textile and boiler. In [6] the techniques used to texture analysis and defect detection are discussed in four categories, statistical approaches, Structural approaches, filter based methods, and model based approaches. Table 1 shows a summary list of some of the key texture analysis methods that have been applied to Texture
classification or segmentation. Clearly, statistical and filter based approaches have been very popular.

<table>
<thead>
<tr>
<th>Category</th>
<th>Method</th>
</tr>
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<tbody>
<tr>
<td>Statistical</td>
<td>1. Histogram properties</td>
</tr>
<tr>
<td></td>
<td>2. Co-occurrence matrix</td>
</tr>
<tr>
<td></td>
<td>3. Local binary pattern</td>
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<tr>
<td></td>
<td>4. Other gray level statistics</td>
</tr>
<tr>
<td></td>
<td>5. Autocorrelation</td>
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<tr>
<td></td>
<td>6. Registration-based</td>
</tr>
<tr>
<td>Structural</td>
<td>1. Primitive measurement</td>
</tr>
<tr>
<td></td>
<td>2. Edge Features</td>
</tr>
<tr>
<td></td>
<td>3. Skeleton representation</td>
</tr>
<tr>
<td></td>
<td>4. Morphological operations</td>
</tr>
<tr>
<td>Filter Based</td>
<td>1. Spatial domain filtering</td>
</tr>
<tr>
<td></td>
<td>2. Frequency domain analysis</td>
</tr>
<tr>
<td></td>
<td>3. Joint spatial/spatial-frequency</td>
</tr>
<tr>
<td>Model Based</td>
<td>1. Fractal models</td>
</tr>
<tr>
<td></td>
<td>2. Random field model</td>
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<tr>
<td></td>
<td>3. Texem model</td>
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</tbody>
</table>

Table 1: Inexhaustive list of textural analysis methods

Since now, doesn’t proposed any accurate approach for porosity detection on stones, also near all of other cases methods don’t provide good severability and dimensionality on stone images between porosity and non-porosity parts.

Local binary pattern (LBP) is an operator for computing local contrast of each pixel. It’s first proposed by Ojala et al [7]. And the improved version of that is offered in [8] some years after. So, in this paper an approach is proposed for porosity detection based on improved local binary patterns. The proposed approach includes two stages. The first stage is train. In this, some absolutely porosity-less images were taken and analyzed by local binary pattern operator and a basis feature vector is provide. Which is a good identicate for non-porosity images. The second stage is test. In this, by extracting improved local binary pattern features of test images and compared them with basis vector, porosity parts are detected.

In the result part, some stone images of different kinds are captured and the proposed approach applied on them. The high detection rate shows the quality of approach. Also low time and money complexity rotate invariant, noise insensitive, and illumination invariant are some of advantages.

1.1 Paper organization:
The reminder of this paper is organized as follows: Section two is related to the Local binary pattern and the way of this estimation. Section three is related to the description of improved version of Local binary pattern (LBP). In section four, the proposed feature extraction method is described. Section five has proposed approach for detecting the porosity. Finally, the results and conclusion included.

2 Local Binary Pattern:
The local binary pattern (LBP) is a non-parametric operator which describes the local spatial structure and local contrast of an image. Ojala et al. [7] first introduced this operator and showed its high discriminative power for texture classification. At a given pixel position \((x_c : y_c)\), LBP is defined as an ordered set of binary comparisons of pixel intensities between the center pixel and its eight surrounding pixels (Fig 2). The decimal form of the resulting 8-bit word (LBP code) can be expressed as follows:

\[
LBP(x_c, y_c) = \sum_{n=0}^{7} s(i_n - i_c)2^n \tag{2}
\]

Where \(i_c\) corresponds to the grey value of the center pixel \((x_c : y_c)\), in to the grey values of the 8 surrounding pixels, and function \(s(x)\) is defined as:

\[
s(x) = \begin{cases} 
1 & \text{if } x \geq 0 \\
0 & \text{if } x < 0 
\end{cases} \tag{3}
\]

By definition, the LBP operator is unaffected by any monotonic gray-scale transformation which preserves the pixel intensity order in a local neighbourhood. Note that each bit of the LBP code has the same significance level and that two successive bit values may have a totally different meaning. Actually, The LBP code may be interpreted as a kernel structure index.

![Fig2. Computation LBP](image)

2.1 Achieving Rotation invariance
According to [7], The LBP8 operator produces 256 (28) different output values, corresponding to the 256 different binary patterns that can be formed by the eight pixels in the neighbor set. When the image is rotated, the gray values \(i_n\) will correspondingly move along the perimeter of the circle around \(i_c\). Since we always assign \(g_1\) to be the gray value of element \((0, 1)\), to the right of \(g_0\), rotating a particular binary pattern naturally results in a different LBP8 value. This does not apply to patterns...
They argue that the larger the uniformity value $U$ of a pattern is, i.e. the larger number of spatial transitions occurs in the pattern, the more likely the pattern is to change to a different pattern upon rotation in digital domain. Based on this argument patterns are designated that have $U$ value of at most 2 as 'uniform' and propose the following operator for gray scale and rotation invariant texture description instead of $LBP^8_{riu2}$.

$$LBP^8_{riu2} = \begin{cases} \sum_{i=1}^{8} s(i_r - i_c) & \text{if } U(LBP_8) \leq 2 \\ 9 & \text{otherwise} \end{cases}$$

Eq. (5) corresponds to giving an unique label to the nine ‘uniform’ patterns illustrated in the first row of Fig. 3 (label corresponds to the number of ‘1’ bits in the pattern), the 27 other patterns being grouped under the ‘miscellaneous’ label (9). Superscript $riu2$ corresponds to the use of rotation invariant "Uniform" patterns that have $U$ value of at most 2.

### 4 Proposed Feature Extraction

The $LBP$ operator can describe and use in a similar way for every size of neighborhoods like $5 \times 5$ or $7 \times 7$ or etc. According to the section 3, by using $3 \times 3$ size for $LBP$ operator, 10 uniform and non-uniform labels are grouped. So, the feature extraction can described based on this labels. To determine the feature vector, first should compute the probability of occurrence of each label in image. Equation (6) shows this:

$$\text{Probability of Label}(K) = \frac{\text{Number of pixels}(LBP = K)}{\text{Size of Image}}$$

So, each dimension of feature vector is one of the labels and that value is the occurrence probability of that label. For example, by using $3 \times 3$ $LBP$ operator, a feature vector can provide which has 10 dimensions. In a similar way, for every $LBP$ operators, feature vector can compute. For example, by using size $5 \times 5$ or $7 \times 7$ for $LBP$, the feature vectors are computed by 16 or 24 dimensions.

### 5 Proposed Approach

According to previous sections, a feature vector can extract for each image or sub-image, which provides good severability and discriminately. So, in this section we describe an approach to detect porosity based on improved local binary patterns. The proposed approach is includes two stages. The first one is train. The aim of train stage is to learn porosity-less images. So, first of all, some absolutely non-porosity images should provide for each kind of stone. Next, the feature vector is
extracted for this train images and the extracted feature names basis vector. In continuous, the train images are divided to same size windows. It's better to use some overlaps between them. After that, feature vectors are extracted for each window. Now, an accurate threshold can compute for non-porosity windows by using (7). In equation(7) the non-similarity amount is calculated between window’s vector and basis vector by Logarithm Likelihood. So, the Maximum value of computed amounts is shown the non-porosity threshold. Equation (8) is shown this. The flowchart of train stage is shown in fig3.

\[ L_k = (S_k, M) = \sum_{i=0}^{P} S_{ik} \log \left( \frac{S_{ik}}{M_i} \right) \quad k = 1, \ldots, N \quad (7) \]

Where, \( S_k \) is the feature vector which extracted for \( K_{th} \) Window and \( M \) is the basis feature vector. Also, \( N \) is the number of windows and \( i \) means the \( i_{th} \) dimension of feature vectors.

\[ T = \max (L_k) \quad k = 1, 2, \ldots, N \quad (8) \]

Where, \( T \) is the non-porosity threshold (porosity-less threshold) and \( L_k \) shows the non-similarity amount between \( k_{th} \) and basis vector.

The second stage is related to test images and porosity detection. First of all, the test image is divided to windows with same size by train windows. (Overlapping may provide better detection). So, for every test images, the feature vector is extracted like train stage. After that, by using equation (7) the non-similarity amount is computed for each one by compare with basis vector. Finally, each window which have non-similarity amount more than train porosity-less threshold is highlighted as porosity window. The flowchart of test stage is shown in fig4. To tuning, the size of windows, an N-folds algorithm is used and the results has been shown that 16×16 is better than another sizes.

**6 Results**

To prove the quality of proposed approach, by using a digital camera (16 Mp), 60 images are taken of 3 kinds of stones. Which name Orange Travertine, Hatchet and Wave -less creamy Travertine. Also, some absolutely porosity less images are captured for train stage. After that some sizes of windows are tested and finally 16×16 is chosen. By using this size for windows, the proposed approach is applied on test Database. Then, to compute the accuracy rate of approach, the detection rate is computed based on equation (9) for every porosity detected image.

\[ \text{Detection Rate} = 100 \times \frac{N_{cc} + N_{dd}}{N_{total}} \quad (9) \]

Where, \( N_{cc} \) shows the number of windows which are really porosity less and the proposed approach detected it as porosity-less window. And the \( N_{dd} \) means the windows which detected as porosity in real image it is porosity. The table2 shows the average of detection rates for each kind of stones. Also it is repeated for each size of local binary patterns such as 3×3, 5×5 and 7×7. The proposed approach is multi resolution one, so the results of each size for LBP operator can mix by another one. The equation (10) shows this.

\[ L_K^n = \sum_{n=1}^{N} L_K(S^n_k, M^n) \quad (10) \]

Where, \( N \) is the number of LBP operators and \( S^n \) and \( M^n \) correspond to the sample extracted with operator \( n=1, 2, \ldots, N \). So, the results of each LBP size are mixed by another and the results shows
in rows number 4, 5, 6 and 7 in table 2, some of the results is shown in fig5.

<table>
<thead>
<tr>
<th>Features</th>
<th>Stone LBP Operator</th>
<th>Creamy Travertine</th>
<th>Hatchet Travertine</th>
<th>Orange Travertine</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>8.3</td>
<td>88.68</td>
<td>91.64</td>
<td>90.02</td>
</tr>
<tr>
<td>18</td>
<td>16.5</td>
<td><strong>93.67</strong></td>
<td>92.27</td>
<td>94.43</td>
</tr>
<tr>
<td>26</td>
<td>24.7</td>
<td>90.05</td>
<td>91.32</td>
<td><strong>95.43</strong></td>
</tr>
<tr>
<td>10 + 18</td>
<td>8.3 + 16.5</td>
<td>93.22</td>
<td>90.53</td>
<td>91.14</td>
</tr>
<tr>
<td>10 + 26</td>
<td>8.3 + 24.7</td>
<td>89.60</td>
<td>89.03</td>
<td>90.75</td>
</tr>
<tr>
<td>18 + 26</td>
<td>16.5 + 24.7</td>
<td>89.44</td>
<td><strong>94.11</strong></td>
<td>92.46</td>
</tr>
<tr>
<td>10 + 18  + 26</td>
<td>8.3 + 16.5 + 24.7</td>
<td>85.54</td>
<td>87.73</td>
<td>91.37</td>
</tr>
</tbody>
</table>

Table2. The accuracy rates of database

![Image](a)
![Image](b)
![Image](c)
![Image](d)
![Image](e)
![Image](f)
![Image](g)
![Image](h)
![Image](i)
Fig5. Some of porosity detected results
(a) Original Image of Creamy non-wavy travertine stone (b) defect detected of (a) by LBP 3×3 (c) defect detected of (a) by LBP 5×5 (d) defect detected of (a) by LBP 3×3 and 7×7 (e) Original Image of Orange travertine stone (f) defect detected of (e) by LBP 3×3 (g) defect detected of (e) by LBP 5×5 (h) defect detected of (e) by LBP 3×3 and 7×7 (i) Original Image of Hatchet stone (j) defect detected of (i) by LBP 3×3 (k) defect detected of (i) by LBP 5×5 (L) defect detected of (i) by LBP 3×3 and 7×7

7 Conclusion
The aim of this paper, is offering an accurate approach for porosity detection in stone. In this respect, in section 2, the local binary pattern is described. In continuation, improved local binary pattern method is described in section 3 to analysis textures of stone images. After that, an algorithm is proposed for feature extraction stage. By using this method, porosity less images are analyzed and trained. So in test stage, the porosity is detected and porosity amount is computed. The results shows the high accuracy of proposed approach in stone defect detection. Low computation complexity provides the proposed approach as an automatic visual inspection system. According to use train stage, the proposed approach can use in every defect detection cases such as textile, ceramic, metallic and etc. Also the proposed approach is not sensitive to low noises, because it uses the local neighbor’s relation.

References