An Efficient Method for Texture Classification with Local Binary Pattern Based on Wavelet Transformation

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Abstract
In this paper, we present an efficient method for texture classification with local binary pattern based on wavelet transformation. We improve the Local Binary Pattern approach with Wavelet Transformation to propose the texture classification. We used four class of Brodatz textures data base for proposed method. Each class is divide to 64 texture image and then wavelet transformation is applied to each texture. After transformed texture from wavelet the feature extraction matrix is formation using LBP. We verify the other method and proposed method is very good and efficient for classification texture image.

Keywords: Local Binary Pattern; Wavelet Transformation; Texture Classification.

1. Introduction
Texture classification is a fundamental issue in computer vision and image processing, playing a significant role in a wide range of applications that includes medical image analysis, remote sensing, object recognition, document analysis, environment modeling, content-based image retrieval and many more [3]. The local binary pattern (LBP) is one of the most used texture descriptors in image analysis. In this paper, we extend the original LBP with continues wavelet transformation for texture analysis and classification. The proposed method presents the comparative results of classification using both feature sets separately and in combination. The paper is organized as follows. In the next section, a brief introduction for demonstrating basic concepts of Local Binary Pattern (LBP) is given. In the section 3 Continues Wavelet Transformation is introduced. In the Section 4 the Feature extraction and proposed method is described and in the section 5 experimental results of this method are given. The conclusion of this paper is given in section 6.

2. Local Binary Pattern
The LBP is an operator that was first introduced by Ojala et al. [1], and has been shown to be an effective descriptor in texture classification [2]. Firstly, the LBP operator labels the pixels of an image by thresholding the 3 x 3-neighborhood of each pixel with the center value and the result as a binary number. Then a decimal number of the binary number is used to label the center pixel. At last, the histogram of the labels can be used as a texture descriptor. Images are probed locally by sampling grayscale values at a central point x0,0 and p points x0,0,...xp-1 spaced equidistantly around a circle of radius r centered at x0,0. Formally,

\[ LBP_{p,r} = \sum_{n=0}^{p-1} s(x_{r,n} - x_{0,0})2^n, \quad s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \]

Figure 1 shows the illustration of the basic LBP operator. Later the operator was extended in two aspects [2].
Fig. 1. The basic LBP operator, (a) Original texture image, (b) Sub-Image, (c) Gray level intensity value, (d) Threshold value with center pixel, (e) Binary pattern Labeled by a decimal number.

The extended LBP operator uses neighborhoods of different sizes and shapes to label each pixel by bilinear interpolation. Because of using circular neighborhood and bilinear interpolation, any radius and number of pixels are chosen in the neighborhood. For neighborhoods we will use the notation (P, R) which means P sampling points on a circle of radius of R. Figure 2 shows some examples of the circularly symmetric neighborhoods.

Fig. 2. Circularly symmetric neighbor sets for different (P, R).

The gray values of neighbors which do not lie precisely in a pixel location may be estimated by interpolation. Given an $N \times M$ image $I$, let $LBP_{p,r}(i,j)$ be the identified LBP pattern of each pixel $(i, j)$, then the whole texture image is represented by a histogram vector $h$ of length $K$:

$$h(k) = \sum_{i=1}^{N} \sum_{j=1}^{M} \delta(LBP_{p,r}(i, j) - k)$$

Where $0 \leq k \leq K - 1$, and $K = 2^p$ is the number of all the LBP codes. Feature $h$ has attractive properties: grayscale invariance, low complexity, few parameters, and satisfactory discriminating power. However, the basic LBP operator produces rather long histograms ($2^p$ distinct values), and it becomes an intractable problem to estimate $h$ due to the overwhelming dimensionality of $h$ with large $p$. Moreover, it is easy to realize that due to the way LBP numbers are created, they are very sensitive to noise. Another extension to the original operator uses the certain local binary pattern termed “uniform patterns” $LBP_{p,r}^{riu}$. A LBP is called uniform if it contains at most tow bitwise transitions or discontinuities from 0 to 1 or vice versa in the circular presentation of the pattern. The improved operator not only possesses a property of gray scale and rotation invariant operator, but also allows for detecting “uniform pattern” at circular neighborhoods of any quantization of the angular space and at any spatial resolution. Both the two properties are important for palm print recognition [2].

$$LBP_{p,r}^{riu} = \begin{cases} \sum_{n=0}^{p-1} s(x_{r,n} - x_{0,0}), & \text{if } U(LBP_{p,r}) \leq 2 \\ p + 1, & \text{otherwise} \end{cases}$$

Where

$$U(LBP_{p,r}) = \sum_{n=0}^{p-1} |s(x_{r,n} - x_{0,0}) - s(x_{r,mod(\theta+1,p)} - x_{0,0})|$$

The superscript $riu2$ denotes the rotation invariant “uniform” patterns that have $U$ values at most 2. Therefore, mapping from $LBP_{p,r}$ to $LBP_{p,r}^{riu2}$ results in only $p+2$ distinct groups of patterns, leading to a much shorter histogram representation.

The four texture classes from the Brodatz album [9] is shown in Figure 3 actually are misclassified by using only the conventional LBP or according to our experimental results.
In the above four textures, they all have the same sets of dominant patterns with very similar proportions, and the pattern type labelled with 24 is one of the dominant patterns. As we can see, the numbers of such dominant patterns in each texture are very close to each other. However, the distribution properties of this pattern in these four texture images are very different with each other. Therefore, the Continuous Wavelet Transformation is a very important property to describe the textures, which will be further illustrated in the Experimental Results section.

3. Continuous Wavelet Transformation

The WT is designed to address the problem of nonstationary signals. It involves representing a time function in terms of simple, fixed building blocks, termed wavelets. These building blocks are actually a family of functions which are derived from a single generating function called the mother wavelet by translation and dilation operations. Dilation, also known as scaling, compresses or stretches the mother wavelet and translation shifts it along the time axis [5,8,10,12].

The WT can be categorized into continuous and discrete. Continuous wavelet transform (CWT) is defined by

$$CWT(a,b) = \int_{-\infty}^{\infty} x(t)\psi_{a,b}^*(t)dt$$

where $x(t)$ represents the analyzed signal, $a$ and $b$ represent the scaling factor (dilatation/compression coefficient) and translation along the time axis (shifting coefficient), respectively, and the superscript asterisk denotes the complex conjugation. $\psi_{a,b}(t)$ is obtained by scaling the wavelet at time $b$ and scale $a$:

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\psi\left(\frac{t-b}{a}\right)$$

where $\psi(t)$ represents the wavelet [8,10].

Continuous, in the context of the WT, implies that the scaling and translation parameters $a$ and $b$ change continuously. However, calculating wavelet coefficients for every possible scale can represent a considerable effort and result in a vast amount of data.

4. Feature extraction and proposed algorithm

A feature is a distinctive or characteristic measurement, transform, structural component extracted from a segment of a pattern. Features are used to represent patterns with the goal of minimizing the loss of important information. The feature vector, which is composed of the set of all features used to describe a pattern, reduces the dimensional space needed to represent that pattern. This, in effect, means that the set of all features that could be used to describe a given pattern (a large and in theory an infinite number as very small changes in some parameters are allowed to separate different features) is limited to those actually represented in the feature vector. In addition, the classification often becomes more accurate when the pattern is simplified by including important features or properties only [4–5]. A feature extraction is the determination of a feature or a feature vector from a pattern vector. In order to make pattern processing problems solvable one needs to convert patterns into features, which become condensed representations of patterns, ideally containing only salient information. Feature extraction methods could be based on either calculating statistical characteristics or producing syntactic descriptions. The feature selection process usually is designed to provide a means for choosing the features which are best for classification optimized against on various criteria. The feature selection process performed on a set of predetermined features. Features are selected based on either (1) best representation of a given class of texture, or (2) best distinction between classes. Therefore, feature selection plays an important role in classifying systems such as neural networks. For the purpose of classification problems, the classifying system has usually been implemented with rules using if then clauses, which state the conditions of certain attributes and resulting rules. However, it has proven to be a difficult and time consuming
method. From the viewpoint of managing large quantities of data, it would still be most useful if irrelevant or redundant attributes could be segregated from relevant and important ones, although the exact governing rules may not be known. In this case, the process of extracting useful information from a large data set can be greatly facilitated [8–10]. In the feature extraction stage, numerous different methods can be used so that several diverse features can be extracted from the raw data. The wavelet transform (WT) provides very general techniques which can be applied to many tasks in image processing. Wavelets are ideally suited for the analysis of sudden short-duration image changes.

4.1. Summary of texture classification with LBP based on CWT

Summary of the proposed method in the figure (5) is shown.

![Diagram of the proposed method](image)

5. Experimental Result

The classification accuracies of Timo Ojala et al. approaches under different environments are listed in Table 1. According to the experimental results, the proposed LBP approach can already outperform the other method under different conditions. Also, by embedding the wavelet transformation information of dominant patterns (WTDP) with the LBP, the classification performance is better than using LBP alone.

**TABLE 1**

Proportions (%) of “riu2” for some samples in the Brodatz database.
Patterns for Each Texture Used in the Experiments and Their Average over All Textures

<table>
<thead>
<tr>
<th>Texture</th>
<th>Timo Ojala et al. [2]</th>
<th>Proposed Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grass</td>
<td>P = 8, R = 1</td>
<td>P = 8, R = 1</td>
</tr>
<tr>
<td></td>
<td>P = 16, R = 2</td>
<td>P = 16, R = 2</td>
</tr>
<tr>
<td></td>
<td>P = 24, R = 3</td>
<td>P = 24, R = 3</td>
</tr>
<tr>
<td>Woolen cloth</td>
<td>91.8</td>
<td>92.6</td>
</tr>
<tr>
<td></td>
<td>74.2</td>
<td>95.6</td>
</tr>
<tr>
<td></td>
<td>52.8</td>
<td>90.9</td>
</tr>
<tr>
<td>Brick wall</td>
<td>88.9</td>
<td>95.23</td>
</tr>
<tr>
<td></td>
<td>71.0</td>
<td>93.5</td>
</tr>
<tr>
<td></td>
<td>55.0</td>
<td>91.3</td>
</tr>
<tr>
<td>weave</td>
<td>76.6</td>
<td>85.65</td>
</tr>
<tr>
<td></td>
<td>50.9</td>
<td>91.9</td>
</tr>
<tr>
<td></td>
<td>32.1</td>
<td>95.6</td>
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<tr>
<td>Average</td>
<td>85.7</td>
<td>92.24</td>
</tr>
<tr>
<td></td>
<td>64.85</td>
<td>91.6</td>
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<tr>
<td></td>
<td>46.375</td>
<td>90.27</td>
</tr>
</tbody>
</table>

6. Conclusion

In this paper, we have proposed an efficient method for texture classification with local binary pattern based on wavelet transformation. Also, we find that the wavelet transformation of dominant patterns (WTDP) actually is a very powerful feature for describing the characteristics of the texture image as it includes the location information of the dominant patterns in the texture images. It has been evaluated by comparing with Timo Ojala et al. approaches with Brodatz databases. It is experimentally shown that our approach has excellent performance in texture classification and is very robust to histogram equalization and random rotation.
Computational simplicity is another advantage of our proposed method as the features can be obtained with only a few calculations and comparisons without the need of performing any image filtering.

References


