Illumination and Rotation Invariant Texture Representation

Xiangyan Zeng, Masoud Naghedolfeizi, Sanjeev Arora,
Nabil Yousif, Ramana Gosukonda, Dawit Aberra
Department of Mathematics and Computer Science, Fort Valley State University, Fort Valley, GA, USA

Abstract— *In this paper, we propose a new feature for texture representation that is based on pixel patterns and is independent of the variance of illumination and rotation. A gray scale image is transformed into a pattern map in which edges and lines used to characterize the texture information are classified by pattern matching. The Gabor filters can enhance edge features, however, are not effective in edge pattern classification. We extract the pattern templates from image patches by Principal Component Analysis (PCA). Based on the pattern maps, the feature vector is comprised of a sorted histogram. The calculation of the features is simple and computationally efficient compared with other illumination and rotation invariant texture schemes*

Keywords: texture representation, pattern matching, principal component analysis (PCA), PCA pattern histogram

1. Introduction

Texture analysis is important for many research topics of computer vision and pattern recognition. Two main categories of techniques are texture classification and texture segmentation, which have applications in content-based image retrieval, surface inspection, remote sensing and medical image analysis. In the real world problems, textures occur irregularly at arbitrary resolutions and orientations with possibly varied illumination. Therefore, an effective texture measure should be resolution, gray-scale and rotation invariant. For texture segmentation problems, low computational complexity is another important consideration.

In the last two decades, many algorithms have been proposed for texture analysis. The research work can be categorized into three lines, including statistical analysis[1], filtering including wavelet transform [2][3], and local pattern methods[4][5]. Some have incorporated at least one property of resolution, gray-scale and rotation invariance. For instance, methods based on local patterns generally construct the features from the pattern of a small neighborhood (3x3 or 5x5) instead of pixel gray scale values and naturally remove the illumination variance influence. An up-to-date successful representative is the methods based on the local binary pattern (LBP). These methods obtain the feature vector from the histogram of binary patterns representing comparison of pixels gray scales in a circular local neighborhood. Rotation invariance is achieved by either circularly shifting the circles or performing a global match of the histograms.

In this paper, we extend a method that was proposed in [6] for texture representation that is very simple to calculate and free of the influence of illumination and rotation. A gray scale image is first transformed into a pattern map in which edges and background pixels are classified by pattern matching which is implemented by convolution. Fast Fourier transform can speed up this operation. Then, the feature vector is obtained from the sorted histogram of the pattern map within the texture window. The local spatial feature is extracted through pattern matching and structural rotation effect is removed by sorting the histogram. The statistics of this one map is much simpler than the up-to-date rotation invariant texture features.

To get a pattern map, we need to design a set of pattern templates and assign a pixel to a pattern that matches the neighbor region best. Gabor filter bank can extract texture features, however, it is demonstrated by our experiments that Gabor filters [7] are not effective as the pattern templates in the case that the textures are irregular and non-periodic. A natural way to get the templates is to analyze the image coding process and utilize the basis functions. We apply PCA to nature scene patches and use the basis functions as templates for pattern matching. The differences between these PCA basis functions and those of gradient operators are in that: instead of being designed by mathematics, they are obtained from the statistical analysis and represent the neighbor relationship of real images. As we will see in the following sections, pattern maps obtained by using PCA basis functions generally reflect edge and line features rather well. Hence PCA basis functions are good candidates for templates in pattern matching.

This paper is organized as follows. Section 2 briefly describes the background of texture representation using local binary patterns. In section 3, a texture feature based on pattern maps is proposed for texture representation. In section 4, experimental results are presented to demonstrate the effectiveness of the new method. Section 5 gives the conclusion.

2. Texture Feature Extraction by Local Binary Pattern (LBP)

2.1 Illumination invariant LBP

LBP is a texture descriptor for gray scale images. In the following discussion of LBP, we assume that a local neighborhood is centered on pixel g_c. The P pixels in the neighborhood form a clockwise circular chain with a radius R and are indexed as $(g_0, g_1, \ldots, g_{P-1})$. LBP feature is illumination invariant. For each pixel g_c , the gray scale value is first transformed into a binary chain through thresholding:

$$(s(g_0 - g_c), s(g_1 - g_c), \ldots, s(g_{P-1} - g_c)) \tag{1}$$

where

$$s(x) = \begin{cases} 1 & x > 0 \\ 0 & x < 0 \end{cases} \tag{2}$$

And the LBP feature of the pixel is obtained by multiplying each binary value with a binomial factor:

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p \tag{3}$$

After identifying the LBP pattern of each pixel, a $N \times M$ texture image is represented by the histogram:

$$H(k) = \sum_{i=0}^{N} \sum_{j=0}^{M} f(LBP_{P,R}(i,j), k), \quad k \in [0, K] \tag{4}$$

where

$$f(x,y) = \begin{cases} 1 & x = y \\ 0 & otherwise \end{cases} \tag{5}$$

and $K = 2^P$ is the maximum LBP pattern value. $H(k)$ quantifies the frequency of individual patterns corresponding to certain micro-features and represents the spatial structure of textures in the image.

2.2 Rotation invariant LBP

The LBP feature was modified to achieve rotation invariance.

$$LBP_{P,R}^{ri} = min\{ROR(LBP_{P,R}, i), i = 0, 1, \ldots, P-1\} \tag{6}$$

where $ROR(x, i)$ performs a circular bit-wise right shift i times on the P bits of x.

2.3 Uniform patterns in LBP

The pattern value range in the above LBP is very wide. It has shown that LBP with the full range of patterns does not provide good discrimination[4]. It has been noticed that certain patterns are fundamental properties of textures. They are the “uniform” patterns which have very few (≤ 2) 0/1 bitwise transitions. For patterns of 8 bits, 00001000 has 2 bitwise transitions and is a uniform pattern, while 00101000 is not because it has 4 transitions. The number of “uniform” patterns is very manageable. For instance, 8 bits only have 9 distinct “uniform” patterns: 00000000, 00000001, 00000011, 00000111, 00001111, 00011111, 00111111, 01111111, and 11111111. These patterns can be represented by the numbers of ‘1’s regardless of their locations. Therefore, the binomial factor in Equ. (3) is not needed. The new LBP descriptor that only uses the “uniform” patterns and is rotation invariant is defined as:

$$LBP_{P,R}^{uri} = \begin{cases} \sum_{p=0}^{P-1} s(g_p - g_c) & U(LBP_{P,R}) \leq 2 \\ P+1 & otherwise \end{cases} \tag{7}$$

where the U value of an LBP pattern is defined as the number of 0/1 bitwise transitions in that pattern

$$\begin{aligned} U(LBP_{P,R}) = &\left| s(g_0 - g_c) - s(g_{P-1} - g_c) \right| \\ &+ \textstyle\sum_{p=1}^{P-1} \left| s(g_p - g_c) - s(g_{p-1} - gc) \right| \end{aligned} \tag{8}$$

“Uniform” patterns resemble flat areas and edges of varying curvature in images. “Nonuniform” patterns generally have much low frequency and will be grouped into one bin in the histogram.

3. A New Feature for Texture Representation

3.1 Texture feature extraction by pattern matching

In this section, we propose a new template pattern feature extraction method. The idea is also representing image textures by the frequency of certain patterns. However, the patterns are solid instead of consisting of only rim pixels as in LBP. Pattern labels are obtained through a template matching process.

A gray scale image is first transformed into a pattern map in which edges and background pixels are classified by pattern matching. Given a gray scale image $\mathbf{X}$, convolution is performed with a set of K pattern templates of size $S \times S$ $\{\mathbf{w}_i, \quad i = 1, \ldots, K\}$,

$$\mathbf{C}_i = \mathbf{w}_i * \mathbf{X} \tag{9}$$

The pattern label of a pixel (i, j) is obtained:

$$\mathbf{PL}(i,j) = k \tag{10}$$

where

$$\mathbf{C}_k(i,j) = max\{\mathbf{C}_l(i,j), \quad l = 1, \ldots, K\} \tag{11}$$

The value of a pixel in the pattern map PL is the pattern label of its neighborhood in the original gray scale image $\mathbf{X}$. After identifying the pattern of each pixel, a $N \times M$ texture image is represented by the histogram of patterns:

$$His(k) = \sum_{i=1}^{N} \sum_{j=1}^{M} f(PL(i,j), k), \quad k \in [1, K] \tag{12}$$

where

$$f(x,y) = \begin{cases} 1 & x = y \\ 0 & otherwise \end{cases} \tag{13}$$

Fig. 1: 348×348 nature scene images

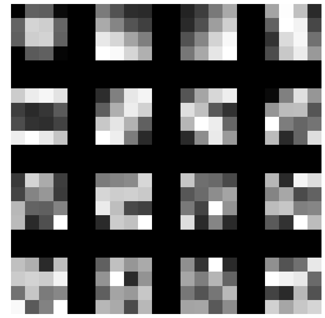


Fig. 2: Sixteen 4×4 PCA basis functions

3.2 Rotation invariant texture feature

The above feature is easily modified to achieve rotation invariance. Pixels assigned to the same pattern will be assigned to another but still the same pattern after rotation. Based on this observation, a sorted histogram is rotation invariant.

$$SORT\left(His\left(k\right)\right), \quad k \in [1, K] \tag{14}$$

3.3 Pattern templates obtained by principal component analysis

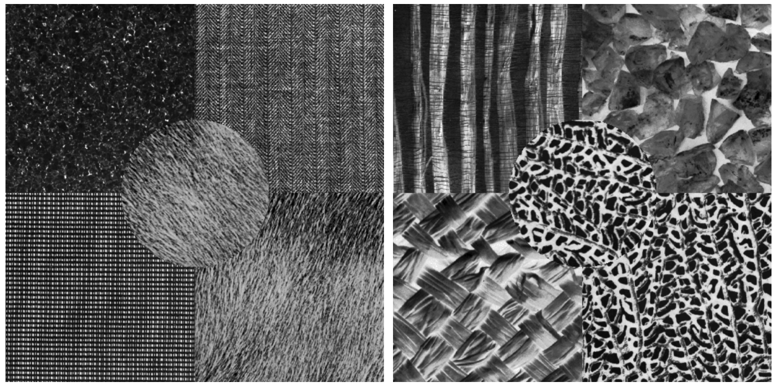
Pattern templates represent the spatial features in an image and reflect that how a pixel is related to its neighboring pixels. A common method in statistics for analyzing inter-relations between variables is principal component analysis (PCA). Imagine that each image has been formed by a linear combination of basis functions that are the same for all images. The basis functions obtained from principal component analysis of a series of image patches represent the general relationship among neighboring pixels. Hancock has conducted principal component analysis of natural images and found that the basis functions resemble the derivatives of Gaussian operators [8]. In our work, PCA basis functions are used as the templates in the pattern matching process. We randomly choose 15000 4×4 block samples from two 348×348 nature images shown in Fig. 1 and obtain sixteen basis functions shown in Fig. 2. An important question concerns the selection of templates. Since PCA basis functions are sorted in order of decreasing variances, the templates of lower spatial frequencies account for the main part of the variance and are located in the front. It is logical to select the first several PCA templates which represent the most dominant relationships. The first basis is a Gaussian operator and is excluded in pattern matching.

4. Experimental Results

To demonstrate the effectiveness of the new texture feature extraction algorithm, we conducted simulation experiments of texture segmentation and compare the results with those of rotation invariant LBP. In the texture classification phase, different similarity measures have been used in the literature. In the segmentation circumstance, we use K-means which is a simple and efficient way to cluster data. In all the cases, we assume the number of cluster is known a priori.

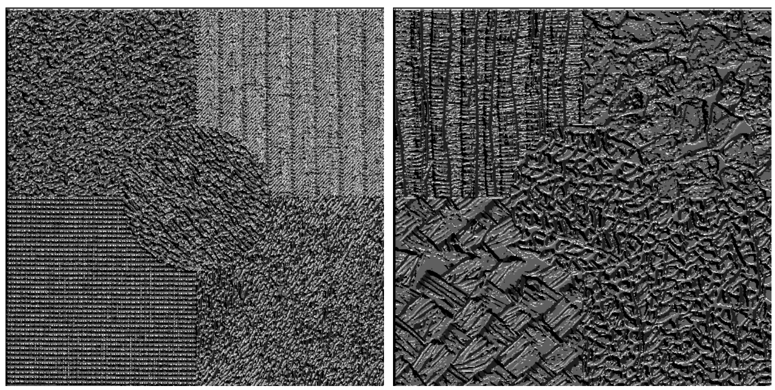
Two images of 512×512 shown in Fig. 3 were tested in the experiment. The first image has five small scale textures which are relatively regular, while the second image has large scale textures. Both images contain a center portion which is a rotated texture. We selected the first 10 PCA templates except the Gaussian filter to transform the gray scale images into pattern maps. Template matching was performed using PCA basis functions and the pattern maps are shown in Fig. 4. Even though the value range of PCA pattern maps is much smaller than that of the original gray scale images, the structure of the textures are visually clear. The illumination variance in the fourth quadrant of image1 was removed in the corresponding PCA pattern map as shown in Fig. 4 (a). Based on the PCA pattern maps, the feature defined in Section 3.2 was determined within a $N \times M$ neighborhood window of each pixel, and the K-means algorithm was used for clustering the feature vectors into 4 classes. To focus on the spatial structure characteristics in texture classification/segmentation, we discarded the contrast (i.e. gray-scale variance) used in other related works [4][5]. We also segmented the images using rotation invariant $LBP_{8,1}$, and $LBP_{16,2}$. The segmentation results of the two images using the three texture descriptors are shown in Fig. 5 and 6, in which white dotted lines are displayed to show the boundaries between textures. Most misclassified pixels are near the boundaries of textures, which can be alleviated by more sophisticated classification methods.

As shown in the results, $LBP_{8,1}$ was very effective in discriminating small scale textures but not large scale textures. For the second image with larger scale textures, $LBP_{16,2}$ was used to achieve reasonable segmentation result. With the similar classification performance, the texture feature of LBP methods was much more computationally intensive. This is due to the complicated pixel-based operations for obtaining the pattern labels. In the meantime, the template matching in the proposed method is basically a convolution process, which is very fast and the computation time does not increase



(a) (b)

Fig. 3: Original texture images (a) image1, (b) image2



(a) (b)

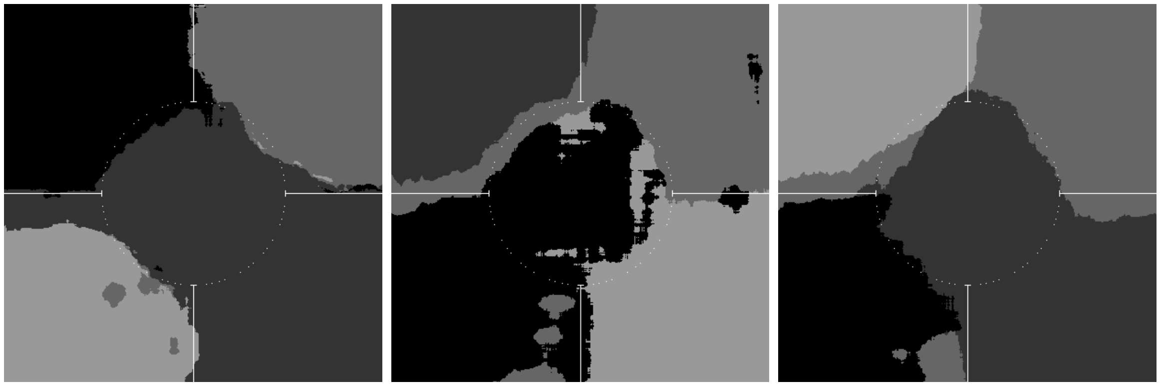
Fig. 4: PCA maps of (a) image1, (b) image2

(a) (b) (c)

Fig. 5: Segmentation results of image1 with a texture window of 60×60.
(a) the proposed feature, (b) $LBP_{8,1}$, (c) $LBP_{16,2}$

significantly with a different template size. The computation time of the three texture features for an image of 512×512 is shown in Table 1, which includes three different feature window sizes.

The feature window size affected the segmentation accuracy as it does in other segmentation approaches. In this experiment, we compared the performance of the three texture descriptors using 60×60, 80×80, and 100×100



(a) (b) (c)

Fig. 6: Segmentation results of image2 with a texture window of 100×100.
(a) the proposed feature, (b) $LBP_{8,1}$, (c) $LBP_{16,2}$

windows. The results are shown in Table 2 and 3. It is noted that smaller windows give better results for small scale textures in the first image, and larger windows yield better results for large scale textures in the second image.

5. Conclusion

Illumination and rotation invariance are highly desired for texture analysis in real world problems. Most approaches achieve these properties at the cost of intensive computation. This paper proposed a method that is simple yet effective in discriminating texture images. Using PCA basis functions of nature images as pattern templates can extract edges which are important components of textures. Sorting the histogram of pattern labels provides invariance to rotation. Compared to LBP methods whose computational cost dramatically increase with the neighborhood size, the proposed method is computational efficient for pattern templates of different sizes. The proposed texture feature can be used for texture segmentation and classification. The simulation experiments in texture segmentation indicated that it may be complementary to LBP in discriminating large and irregular textures. A future research direction is to combine both to achieve the best performance.

Table 1: Computation time (sec.) for an 512×512 image.

Feature window size	Proposed feature	$LBP_{8,1}$	$LBP_{16,2}$
60×60	3.83	25.64	30.61
80×80	6.63	44.6	54.38
100×100	9.99	67.3	82.26

Table 2: Classification error of Image1 $(\%)$.

Feature window size	Proposed feature	$LBP_{8,1}$	$LBP_{16,2}$
60×60	4.28	3.98	3.75
80×80	5.45	4.08	4.89
100×100	7.11	4.29	6.06

Table 3: Classification error of Image2 $(\%)$.

Feature window size	Proposed feature	$LBP_{8,1}$	$LBP_{16,2}$
60×60	11.91	21.27	11.29
80×80	7.59	22.24	9.66
100×100	7.29	21.96	8.83

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