Image Texture Segmentation Using Local Binary Pattern and Color Information: A Comparison

Sara Arasteh[1], Chih-Cheng Hung[1] and Bor-Chen Kuo[2]

[1]*School of Computing and Software Engineering,*
Southern Polytechnic State University, Marietta, GA,30060-2896
{sarasteh, chung}@spsu.edu
[2]*Graduate School of Educational Measurement and Statistics*
National Taichung University, Taichung, Taiwan
kbc@mail.ntcu.edu.tw

ABSTRACT

Image texture and color are important features for image segmentation. Several algorithms have been proposed using color features, texture features or combination of color and texture features for image segmentation in the literature. One of the important issues is how well these algorithms work on differentiating among different textures and colors. In this study, we analyze and compare some of the simple but powerful texture classifiers to explore their strengths and weaknesses in the classification of different type of textures. Texture Spectrum (TS) and Uniform local binary pattern (ULBP) are compared. In order to see the influence of color features in classification process, the combination of ULBP and color is also compared with ULBP and TS in our experiments. Co-occurrence probabilities (GLCPs) are used as a benchmark for the evaluation.

1. INTRODUCTION

Human beings have been using texture in the interpretation of targets of interest in aerial photographs for many years. Therefore, image texture classification plays an important role in computer processing of remotely sensed images. An image segmentation algorithm is in either a pixel-based or a region-based approach. In a region-based approach, the image has to be segmented into homogeneous regions, and a set of meaningful features has to be defined. Once defined, image regions (blocks) can be categorized using pattern recognition techniques. In a pixel-based segmentation, spectral information is used to classify each pixel in the image. One of the main drawbacks of the per-pixel segmentation is that each pixel is treated independently without consideration for its neighbors. Spectral, textural, and contextual information are three fundamental pattern elements used in human interpretation of color photographs [1]. By using these three types of information, more features about an object can be extracted. This should result in a better segmentation.

Texture analysis methods are usually categorized into four approaches: 1) structural, 2) statistical, 3) model-based and 4) transform-based. In the structural approach [2] texture is represented by a hierarchy of spatial arrangements of defined primitives called microtextures. To describe the texture, the basic primitive patterns and their replacement rule have to be defined. The statistical methods analyze the spatial distribution of gray values in the image and derive a set of statistics from the distribution of local features [3]. In model-based texture analysis, texture is characterized by a set of parameters representing an analytical model [4]. The transform methods of texture analysis, such as Fourier [5], Gabor [6] and wavelet transforms [7], produce an image in a space whose coordinate system has an interpretation that is closely related to the characteristics of a texture (such as frequency or size).

In many image segmentation methods color is an important feature in recognition an object. However, due to the texture on the object which has variety insensitive surfaces, in some situation the recognition task might be difficult. On the other hand, segmentation based purely on texture features gives homogenous regions but results in fuzzy boundaries. By combining color and texture features, the advantages of both color and texture based segmentation can be well preserved.

In this study, we used the color and texture segmentation method that we proposed in [8] to analyze the contribution of color in texture segmentation. In our design of image segmentation both texture and color features are extracted first. Then the minimum distance classifier is used for texture and color features classification. Texture features are extracted from local distribution of ULBP value around each pixel. Color features are pixels RGB (or HSV) values. In our experiments the results of this method are compared with Uniform Local Binary Pattern (ULBP), Texture Spectrum, and Co-occurrence probabilities (GLCPs).

This paper is organized as follows; the Uniform Local Binary Pattern (ULBP), Texture spectrum, and Co-occurrence probabilities are described in Section 2, 3, 4 respectively. The combination of ULBP and colors is illustrated in Section 5. Experimental results are presented in Section 6. Conclusion and discussion then follow in Section 7.

2. UNIFORM LOCAL BINARY PATTERNS (ULBP)

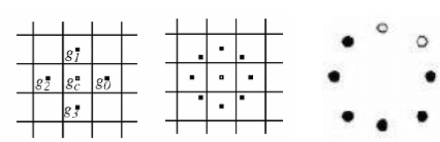
Most approaches for texture classification assume that the unknown samples are similar to the training samples with respect to spatial scale, orientation, and gray-scale properties [9]. However, real-world textures can occur at arbitrary spatial resolutions and rotations. This has motivated the research towards using a rotation invariant approach. Some approaches on rotation invariant texture description include generalized cooccurrence matrices [10], polarograms [11], and texture anisotropy [12].

Another approach is Rotation Invariant Local Binary Pattern [9]. In a general case, the $LBP_{P,R}$ operator, that characterizes the spatial structure of the local image texture, is based on a circularly symmetric neighbor set of P members on a circle of radius R as shown in figure 1. The $LBP_{P,R}$ number is defined as [9]:

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

where,

$$s(x) = \begin{cases} 1 \; if \;\; x \geq 0 \\ 0 \; if \;\; x < 0 \end{cases} \qquad (2)$$



(P=4, R=1) (P=8, R=1)

(a) (b) (c)

Figure1: a,b) Circularly symmetric neighbor sets , c) A sample of uniform patterns with 2 transitions from 0 to 1.

When the image is rotated the gray values g_p (Equation 1) will move along the perimeter of the circle around g_0. In order to remove the effect of rotation rotation invariant local binary pattern is defined as follows [9]:

$$LBP^{ri}_{P,R} = \min\{ROR(LBP_{P,R}, i) \quad | \quad i = 0,1,...,P-1\} \quad (3)$$

Where ROR(x,i) represents a circular bit-wise right shift on P-bit number x i times. It is observed that certain local binary patterns are the majority, sometimes over 90 percent, of all 3×3 neighborhood pixels present in the observed textures. These primary patterns are called "Uniform". The Uniform patterns only contains at most 2 transitions from 0 to 1 as shown in Figure 1c. In Figure 1c, the black and white circles correspond to bit values 0 and 1, respectively. By this definition, using Equation 4, the pattern is called uniform with U value which is less than 3. As a result the $LBP^{riu}_{P,R}$ texture operator (Equation 5) detects "Uniform" local binary patterns at circular neighborhoods of any quantization of the angular space and at any spatial resolution [9].

$$U(LBP_{P,R}) = \left| s(g_{P-1} - g_c) - s(g_0 - g_c) \right| + \sum_{p=1}^{P-1} \left| s(g_p - g_c) - s(g_{p-1} - g_c) \right| \qquad (4)$$

$$LBP^{riu}_{P,R} = \begin{cases} \sum_{p=0}^{P-1} s(g_p - g_c) & if \; U(LBP_{P,R}) \leq 2 \\ P+1 & otherwise \end{cases} \qquad (5)$$

According to Equation 5, there are exactly P+1 uniform binary patterns in a circularly symmetric neighbor set of P pixels and Equation (5) assigns a unique label to each of them. Histogram of uniform binary patterns can be used to measure similarity or dissimilarity of textures. In this study, we used P=8, R=1, for texture features extraction, in our experiments.

3. TEXTURE SPECTRUM

He and Wang stated that a texture image can be decomposed into a set of essential small units called texture units [13][14]. A texture unit is represented by a 3x3 window. The central pixel X_0 in the window is the currently being processed pixel, and the given neighborhood of X_0 (in a symmetric 3x3 window) can be denoted as X={X_1, X_2, X_3…., X_8}. The corresponding texture unit for each X_i is E_i such that:

$$E_i = \begin{cases} 0 & \text{if } X_i < X_0 \\ 1 & \text{if } X_i = X_0 \\ 2 & \text{if } X_i > X_0 \end{cases} \quad \text{for } i = 1, 2, ...8. \qquad (6)$$

The texture unit number can be calculated as:

$$N_{TU} = \sum_{i=1}^{8} E_i * 3^{i-1} \qquad (7)$$

So N_{TU} has 3^8 = 6561 standard textural units which are considered the smallest unit covering all aspects in all eight directions from the central pixel. Texture Spectrum (TS) is the occurrence distribution or the frequency of the texture unit numbers.

Once the texture features are extracted by using the Texture Spectrum, most classification algorithms can be used to discriminate the texture patterns. The simplest procedure using a supervised classification and minimum distance was provided by He and Wang [13].

4. GRAY-LEVEL CO-OCCURRENCE PROBABILITIES (GLCPs)

Gray-Level Co-occurrence Probabilities (GLCPs) is a statistical method which measures the dependence between pairs of gray-level of pixels in a specified spatial relation.

The spatial relationship between pixels and their neighbors are recorded into Gray-level Co-occurrence Matrices (GLCMs) and then are used to compute the statistics [15][16]. The preferred statistics that produce independent features are dissimilarity (D), entropy (E), and correlation (C) [13]. These features will be mapped into corresponding feature vectors, and the K-means is used to cluster these vectors.

GLCM is a 2D array whose each element p(i, j) represents the frequency of occurrences of pair pixels separated by distance δ and angle α. Let K be the maximum gray value for the image with size MxN. Element p(i,j) at distance δ and angle α can be found by counting the event {w(m,n)=i, w(m + αδ, n + αδ)=j} where m =0…M-1, n=0…N-1, α=0,45,90 and 135 degree, and $\delta \in R$. Suppose Q is the number of pairs of pixels separated by δ and α. The probability of p(i, j) is the number in p(i, j) divided by Q.

From the GLCM, the features statistic can be computed from equations (8), (9), and (10).

Dissimilarity:

$$D = \sum_{i=1}^{K} \sum_{j=1}^{K} p(i,j) / [1 + |i - j|] \quad (8)$$

Entropy:

$$E = -\sum_{i=1}^{K} \sum_{j=1}^{K} p(i,j) * \ln[p(i,j)] \quad (9)$$

Correlation:

$$C = \sum_{i=1}^{K} \sum_{j=1}^{K} [(ij)\, p(i,j) - \mu_x * \mu_y] / (\sigma_x * \sigma_y) \quad (10)$$

Where μ is the mean, σ is the standard deviation, x is row, y is column, and K is the maximum gray value.

These feature statistics later will be mapped into corresponding feature vectors, and the segmentation can be done by using any clustering techniques. In this case, to make it simple, the K-means is used to cluster these vectors into separated classes.

5. A COMBINATION OF ULBP AND COLORS

In this method that is proposed in [8], we employ both color and texture features for segmentation. As mentioned in section 2, in $LBP_{8,1}$ we have 9 uniform patterns. All non-uniform patterns are considered as one category. Therefore we will have 10 types of ULBP patterns. Using normalized local histogram of these patterns around each pixel in a defined window, texture features are defined for each pixel. Color features are pixels RGB (or HSV) values. Let x_i denotes a feature vector for pixel *i*. Then feature vector, x_i, is defined as $\left([\hat{R}_i, \hat{G}_i, \hat{B}_i], [\hat{t}_{i,0}, \hat{t}_{ji1}, .., \hat{t}_{ji9}]\right)$ in which $\hat{t}_{i,j}$ is the local distribution of Uniform pattern *j* around pixel *i*. Segmentation is done using K-means on feature vectors. Pixel *i* is assigned to nearest cluster (i.e. cluster *m*) with minimum distance measure such that,

$$Diff_{total_{i,m}} = \min\left\langle Diff_{total_{i,1}}, Diff_{total_{i,2}}, .., Diff_{total_{i,k}} \right\rangle \quad (12)$$

Where $Diff_{total_{i,j}}$ is defined as a combination of color and texture measure as follows [8]:

$$Diff_{total_{i,j}} = \sqrt{\alpha^2 \times Diff^2_{RGB_{i,j}} + Diff^2_{texture_{i,j}}}, \quad (13)$$

In equation (13), $Diff_{RGBi,j}$ and $Diff_{texture_{i,j}}$ are color and texture vectors distances respectively and are defined in equations (14) and (15). α is a weighting coefficient that is used to adjust the contribution of texture and color features in the total distance.

$$Diff^2_{RGBi,j} = \frac{1}{NC^2}\left[(R_i - \hat{R}_j)^2 + (G_i - \hat{G}_j)^2 + (B_i - \hat{B}_j)^2\right] \quad (14)$$

$$Diff^2_{texture_{i,j}} = \frac{1}{NT^2}\sum_{h=0}^{9}(t_{i,h} - \hat{t}_{j,h})^2 \quad (15)$$

NC is cumulative variance of R, G, and B histograms. *NT* is textures cumulative variance. This method is also applied to HSV and IHLS color spaces [8].

5.1. A COMBINATION OF ULBP AND COLOR USING BHATTACHARYA DISTANCE

For the color and texture segmentation described above, Euclidian distance is used to find the texture similarity. As mentioned, the texture features for a pixel is defined as the local histogram of ULBP patterns around that. Therefore we can use Bhattacharya metric to measure similarity between two texture features.

The Bhattacharya measure [17] can be used to compare the similarity between two histograms. Let *[r_1, r_2,.., r_n]* and *[s_1, s_2,.., s_n]* denote the normalized frequencies of bins 1 to n in histograms R and S, respectively. The Bhattacharya similarity metric, *BCH*, between R and S histograms is defined as follows [17]:

$$BCH = \sum_{i=1}^{n}\sqrt{r_i}\sqrt{s_i} \quad (16)$$

BCH is between 0 and 1. *BCH* close to 1 shows that the two histograms are similar. For the case of two identical histograms *BCH* equals to 1. Using *BCH* measure, equation (15) is redefined as:

$$Diff^2_{texture_{i,j}} = 1 - \sum_{h=0}^{9}(\sqrt{t_{i,h}}\sqrt{\hat{t}_{j,h}}) \quad (17)$$

As mentioned, if two histograms are very similar then BCH is very close to 1. As a result, the texture difference calculated in equation (17) becomes smaller. Therefore we can still use equation (15) to find the total color and texture differences.

6. EXPERIMENTAL RESULTS

In this section, experiments were performed with the texture classifiers stated in the previous sections. The algorithms were tested on a set of different textures to examine the effectiveness of the algorithms. Some of the experiments are reported in this section.

In our experiments simple GLCPs are developed. The segmentation results using GLCPs depend on some orientations such as distance, angle, and the number of gray-level. The preferred statistics features used in these experiments were dissimilarity (D), entropy (E), and correlation (C). For orientation, we used the average of $0^\circ, 45^\circ, 90^\circ$, and 135° angles.

In the Texture Spectrum classifier, the texture unit of size 3x3 and the window size of 30x30 were used as He and Wang suggested for optimal classification [13][14]. Similar to texture Spectrum the ULBP uses window size of 30x30.

For combination of ULBP and colors, we demonstrated the results of algorithm in RGB and HSV color spaces. Moreover, the segmentation results using Bhattacharya distance measure and Euclidian distance measure are provided in our experiments. In order to examine the influence of the weighting parameter in the segmentation results, parameter α has been set to different values.

In our experiments, we used a colored texture image. The texture classifiers only work on gray-level version of the image. Figures 2b and 2c show the results of TS and ULBP texture segmentation, respectively. Although the ULBP only uses 9 uniform patterns, the result is satisfactory within the regions. Since the texture features are extracted from the pixels neighborhood window, ULBP and TS segmentation methods can not generate smooth boundaries .The larger value of window size results in inaccurate segmentation near the region boundaries. With smaller window size, the texture features are not accurate and do not extract the neighborhood texture properties. Figure 2d shows the results of GLCPs. The GLCPs classification results depend on the selections of orientations parameters such as distance, angle, and the number of gray-level.

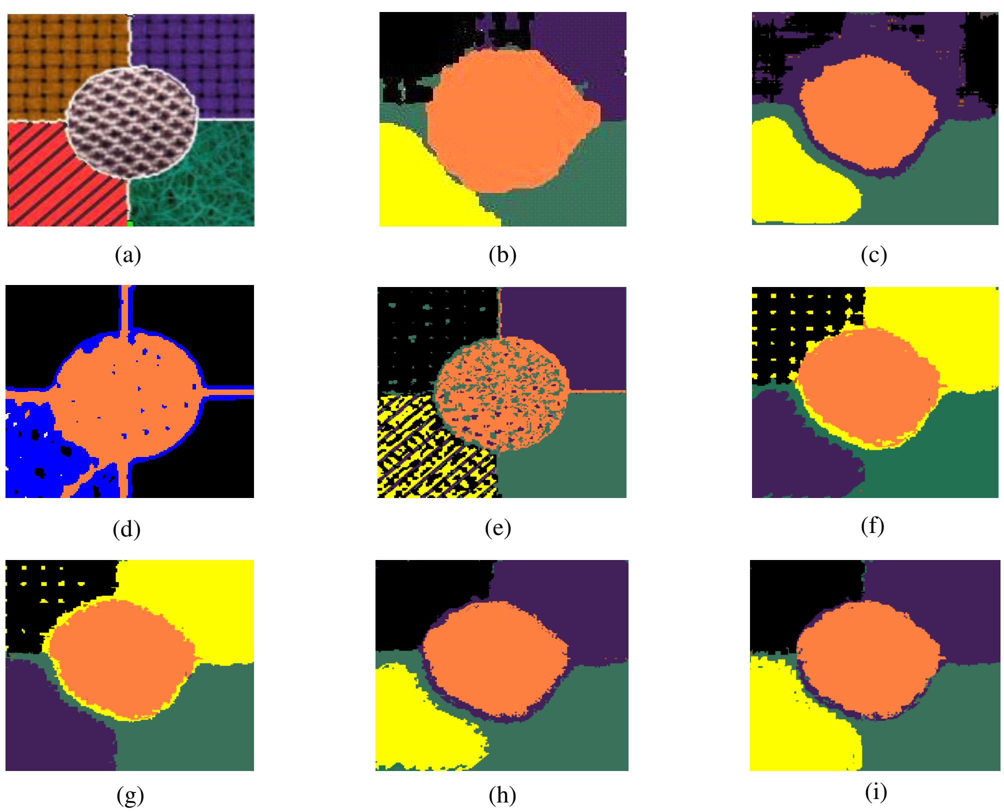


Figure 2: a) An original image, b) Texture segmentation using Texture Spectrum with window size of 30x30, c) ULBP Texture segmentation, with k=5, d) The results of GLCPs with distance=1 and gray-level=8, e) K-means color segmentation results with k=5, f, g, h, and i) Combination of ULBP and color in RGB color space with α =1, k=5, in RGB color space using Bhattacharya distance with α =0.05, k=5, in HSV color space with α =1.5, k=5, in HSV color space using Bhattacharya distance with α =0.05, k=5, respectively.

So far we only used the texture features of the gray-level version of the original image. In order to examine the importance of the color features in these examples, we also applied the combination of ULBP and Colors to the original images shown in figures 2a.

Since we used K-means algorithm for combined ULBP and colors segmentation, we showed the results of the K-means color only segmentation in figure 2e. Figures 2f, 2g, 2h, and 2i show the results of the combination of ULBP and Colors using Euclidian distance and Bhattacharya distance in RGB and HSV color spaces. As illustrated in these figures, HSV color space has better performance in color texture segmentation. On the other hand, using Bhattacharya distance, we can have more accurate results both within and between regions. However, it suffers from some artifacts around the boundaries. As mentioned above, we extract the texture features of each pixel using the texture distribution in a 30×30 neighborhood window around each pixel. As a result, we may have some problems around the boundaries.

7. CONCLUSION AND DISCUSSION

In this paper the Uniform Local Binary Pattern, Texture spectrum, GLCPs, and the combination of ULBP and colors are analyzed and compared. The performance of the GLCPs method depends on the parameters including distance, quantized gray-level orientation and window size. Using a large window size, it not only increases the computation time of the algorithm, but also reduces the spatial resolution of the segmentation. In addition, the window size should be chosen depending on the texture which should be large enough to cover a whole smallest unit of texture or a pattern. The Texture Spectrum and the Local Binary Patterns methods, on the other hand, provide a way to reduce the computation time and the number of parameters, and can achieve satisfactory classification accuracy. Combining ULBP with color also has a good performance based on our experiments. In addition, using both texture and color features together, we can obtain better segmentation results around the boundaries of the objects. From the experiments, using HSV color band for color features along with Bhattacharya measure for texture similarity, improves the segmentation results.

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