SCALE IN VARIANT TEXTURE CLASSIFICATION USING LOCAL LINE BINARY PATTERN AND SVM

Abstract: Texture content plays a prominent role in classification of the image. In this paper we use local line binary patterns for the texture analysis which has high tolerance against illumination variation. Steerable decomposition, a new rotation-invariant and scale-invariant texture representation is used to filter image in four orientations sub bands of the images for feature extraction. Finally, a classifier like SVM, KNN is used for the classification. The experimental results are evaluated for different binary patterns like local binary pattern (LBP), simplified binary pattern (SLBP) and local line binary pattern (LLBP).Comparative analysis shows that LLBP outperforms than the other two binary patterns.

Key words: Local binary pattern, steerable filter decomposition, feature extraction, SVM, KNN

Introduction

Texture classification methods, either explicitly or implicitly, assume that the unknown samples to be classified are identical to the training samples with respect to spatial scale, orientation and gray scale properties. However, real world textures can occur at arbitrary spatial resolutions and rotations and they may be subjected to varying illumination conditions. This has inspired a collection of studies, which generally incorporate invariance with respect to one or at most two of the properties spatial scale, orientation and gray scale, among others [1][2].

Many methods were proposed for scale and rotation invariant image classification, but the natural images do possess this sought of invariance. Chen and kundu [3] and Wu Wei [4] realized gray scale invariance by global normalization of the input image using histogram equalization. This is not a general solution; however, as global histogram equalization cannot correct intra-image (local) gray scale variations. Another problem of many approaches to rotation invariant texture analysis is their computational complexity, which may render them impractical

To overcome the above mentioned issues, in this paper a collective methodology is proposed for both scale and rotation in variance classification. Local binary patterns are used for scale invariance since they are highly tolerated for any illumination changes and steerable filter decomposition [5] is used to apply filters of arbitrary orientation under adaptive control and to examine the filter output as a function of both orientation and Phase this helps in extracting features with rotation invariance.

Local Binary Patterns

The local binary pattern (LBP) texture analysis operator is defined as a gray-scale invariant texture measure, derived from a general definition of texture in a local neighborhood. The local binary pattern (LBP) operator was first introduced by Ojala *et al.* as a complementary measure for local image contrast [6] [7]. Since the LBP was, by definition, invariant to monotonic changes in gray scale, it was supplemented by an orthogonal measure of local contrast. Figure 1 shows how the contrast measure (C) was derived. The average of the gray levels below the center pixel is subtracted from that of the gray levels above (or equal to) the center pixel. Two-dimensional distributions of the LBP and local contrast measures were used as features.

i_0	i_1	i_2
i_3	i_4	i_5
i_6	i_7	i_8

(a)

1	2	4
128	0	8
64	32	16

(b)

Figure 1: (a) LBP operator binary sequence (b) weighted thresholds

So this can described mathematically as

$$LBP(x_c, y_{c)=} \sum_{n=0}^{7} s(i_n - i_c).2^n \qquad (1)$$

Here we illustrate a example

Example Threshold Weights

6	5	2	1	0	0	1	2	4
7	6	1	1	*** ***	0	128	*** ***	8
9	8	7	1	1	1	64	32	16

Patten=11110001

LBP=1+16+32+64+128=241

C=(6+7+8+9+7)/5-(5+2+1)/3=4.7

Simplified local Binary pattern

$$SLBP(x_c, y_{c)=} \sum_{n=0}^{7} s(i_n - i_c).1 \qquad (2)$$

Qian Tao and Raymond Veldhuis [8] proposed simplified local binary pattern (SLBP) for illumination normalization by assigning equal weights to each of the 8 neighborhood. It was shown that the processed image becomes more robust to illumination change. There are two advantages for SLBP: the simplified one is not directional-sensitive and the coding number is largely reduced from 256 to 9 patterns [12].

Local Line binary Pattern

Local Line Binary Pattern (LLBP) is from Local Binary Pattern (LBP) due to it summarizes the local spatial structure (micro-structure) of an image by thresholding. The local window with binary weight and introduce the decimal number as a texture presentation. Moreover it consumes less computational cost [9]. The basic idea of LLBP is similar to the original LBP but the differences are as follows:

1) Its neighborhood shape is a straight line with length **N** pixel, unlike in LBP which is a square shape.

2) The distribution of binary weight is started from the left and right adjacent pixel of center pixel

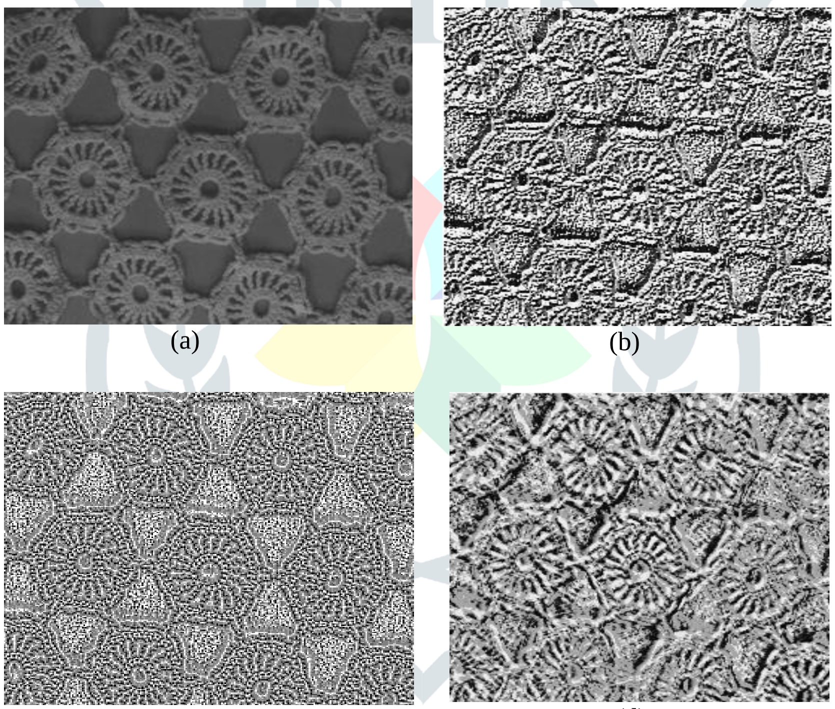
The algorithm of LLBP first obtains the line binary code along with horizontal and vertical direction separately and its magnitude, which characterizes the change in image intensity such as edges and corners, is then computed.

This is expressed mathematically as

$$LLBPh(N,C) = \sum_{n=1}^{c-1} s(h_n - h_c).2^{(c-n-1)} + \sum_{n=c+1}^{N} s(h_n - h_c).2^{(n-c-1)} \quad (3)$$

$$LLBPv(N,C) = \sum_{n=1}^{c-1} s(v_n - v).2^{(c-n-1)} + \sum_{n=c+1}^{N} s(v_n - v_c).2^{(n-c-1)} \quad (4)$$

$$LLBPm = \sqrt{LLBPh^2 + LLBPv^2} \quad (5)$$



(a) (b) (c) (d)

Figure 2: (a) Original Image, Texture content for (b) LBP (c) SLBP (d) LLBP

Steerable filter decomposition and texture representation

Oriented filters are used in many vision and image processing tasks, such as texture analysis, edge detection, image data compression, motion analysis, and image enhancement. In many of these tasks, it is useful to apply filters of arbitrary orientation under adaptive control and to examine the filter output as a function of both orientation and phase. One approach to finding the response of a filter at many orientations is to apply many versions of the same filter, each of which is different from the others by some small rotation in angle[10][5]. Steerable filter is a class of filters in which a filter of arbitrary orientation is synthesized as a linear combination of a set of "basis filters" .The edge located at different orientations in an image can be detected by splitting the image into orientation sub-bands obtained by the basis filters having these orientations. It allows one to adaptively "steer" a filter to any orientation, and to determine analytically the filter output as a function of orientation.

The Steering Constraint is defined as

$$F_\theta(m,n) = \sum_{k=1}^{N} b_k(\theta) A_k(m,n) \qquad (6)$$

Where $b_k(\theta)$ is the interpolation function based on the arbitrary orientation θ which controls the filter orientations. And the basis filters $A_k(m,n)$ are rotated version of impulse response at θ.

$$I(m,n) * F_\theta(m,n) = \sum_{k=1}^{N} b_k(\theta)(I(m,n))A_k(m,n) \qquad (7)$$

Roughly speaking, the texture image can be seen as a set of basic repetitive primitives characterized by their spatial homogeneity. By applying statistical measures, this information is extracted, and used to capture the relevant image content into feature vectors. More precisely, we use the mean μ and standard deviation σ of the energy distribution of the filtered images $S_i(x, y)$(i=1,2,3,4 represent horizontal orientation, rotation of 45°, vertical orientation, and rotation of −45°, respectively), by considering the presence of homogeneous regions in texture images. Given an image I(x,y), its steerable filter decomposition is defined as:

$$s_i(x,y) = \sum_{x1} \sum_{y1} I(x1,y1) B_i(x - x1, y - y1) \qquad (8)$$

Where B_i denotes the directional band pass filters at orientation i=1, 2, 3, 4.

The energy distribution $E_i(x, y)$ of the filtered images $S_i(x, y)$ is defined as

$$E_i = \sum_x \sum_y |s_i(x,y)| \qquad (9)$$

The mean (μ_i) and standard deviation (σ_i) are found as follows:

$$\mu_i = \frac{1}{MN} E_i(x,y) \qquad (10)$$

$$\sigma_i = \sqrt{\frac{1}{MN} \sum_x \sum_y (s_i(x,y) - \mu_i)^2} \qquad (11)$$

So, the corresponding texture feature vector of the original image I(x, y) should be defined as:

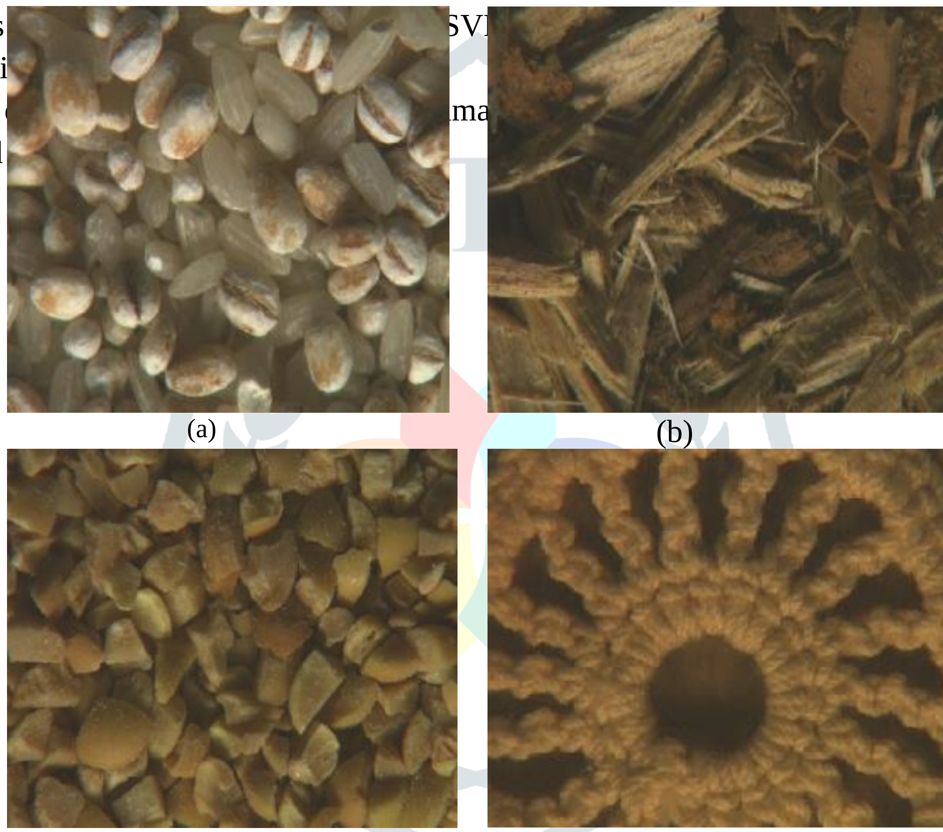
$FT = [\mu_1, \sigma_1, \mu_2, \sigma_2, \mu_3, \sigma_3, \mu_4, \sigma_4]$

PROPOSED METHOD

This is a collective method of LLBP and steerable filter decomposition. In our experiments we have used OUTEX database images available at [11]; these images are captured using Olympus Camedia C-2500 L digital camera of different textures like chips, canvas, wood etc. Some of the test images are displayed below in figure 3. The following are the steps followed in this method (similarity based classification irrespective of the scaling factor).

- Read a set of images of different textures collected from OUTEX database of resolution 256x256

- Apply Binary patterns to obtain the textured images
- Thus, obtained images are passed through steerable filter decomposition and features are extracted forming a $k \times l$ dimensions feature vector. Where "k" is the number of training images and "l" is the features dimension
- Train this … SV… hine Vision Lab. CEERI, Pi…
- Consider … ma… sification rate is calculated…



(a) (b)

(c) (d)

Figure 3: Textured images of OUTEX database (a) barley rice (b) Chips (c) stones (d) canvass

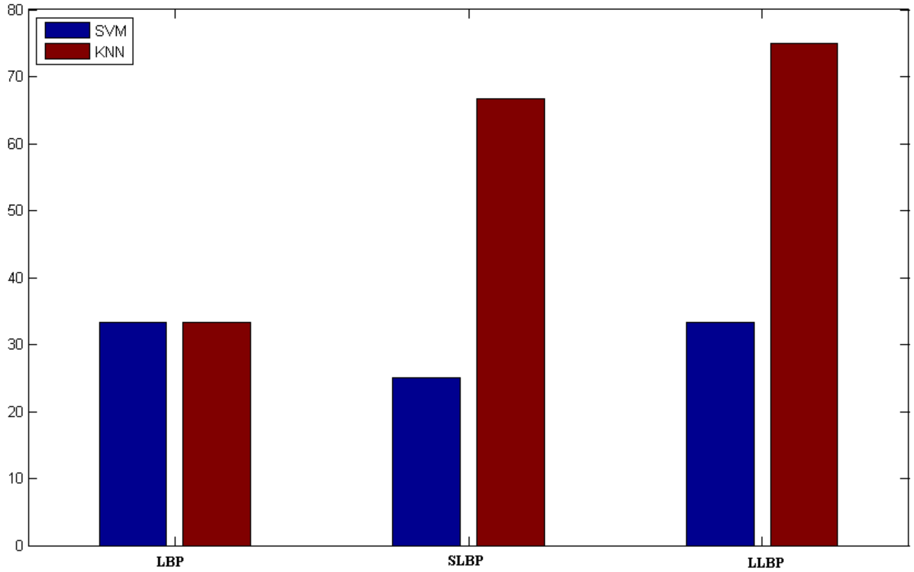


Figure 4: Result analysis for different binary patterns with SVM and KNN

CONCLUSION

In this paper a collective method of binary patterns and steerable filter decomposed is proposed with different binary patterns and classification algorithm. The proposed method is tested with the best of quality textured images and two analysis classification and is been sought .From the above results it can be concluded that the local line binary patter proves to be better in measuring similarity classification. It shows and average increment of classification rate of about 7.2% when compared with simplified local binary pattern analysis. This can be further extended with mere classifying algorithms and block pattern analysis algorithms.

ACKNOWLEDGEMENTS

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