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Texture Analysis using Homomorphic Based Completed Local Binary Pattern

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Abstract: Analysis of images that change with illumination and rotation are very important. The images existing in the real world not uniform due to variations in orientation, scale and illumination. Most of the existing feature extraction methods are affected by noise, change in lighting conditions and rotating angles. This paper presents a method to obtain the texture features named as, Homomorphic based Completed Local Binary Pattern (HCLBP) immune to noise, invariant to illumination and rotation. In this method, to obtain immunity towards noise, the smaller scale features of the texture images are preserved and then the illumination and reflectance components of the images are considered to obtain the histogram features using CLBP. The proposed method was compared with Local Binary Pattern (LBP) and CLBP for the texture images from Outex database . The analysis done using the proposed method yielded better accuracy than LBP and CLBP.

Key Words: Illumination, Reflectance, Orientation, Scale, Homomorphic Completed Local Binary Pattern.

1. INTRODUCTION

Texture analysis methods are utilized in a wide range of applications like remote sensing, automated inspection, medical image processing and document processing [1]. Analyzing a texture is a complex task because of the changes in the arrangement, directionality and randomness of the image [2]. Usually experiments are done with the images taken under uniform conditions. Practically most of the real world applications require images taken under environmental conditions. [3]. Earlier feature extraction methods include Gray Level Cooccurrence Histograms [4], Gray Level Run Length Histograms [5], Markov Random Fields [6],[7], Simultaneous AutoRegressive models [8], Fractal Models [9]. Filters were used to create invariant texture features [10]-[12]. Local Binary Pattern (LBP) [13], a structural method based on the signs of differences of neighboring pixels was very effective for image description. The conventional LBP approach was extended to the Dominant Local Binary Pattern (DLBP) [14] approach in order to effectively capture the dominating patterns in texture images

LBP Variance (LBPV) [15] uses global rotation invariant matching with local variant LBP texture features. Adaptive LBP (ALBP) [16] tried to incorporate local spatial structure into LBP. Completed Local Binary pattern (CLBP) [17] combined local signs, local magnitudes and center gray value. Completed Robust Local Binary Pattern (CRLBP) [18] was produced by replacing the centre pixel by the average local gray level.

The main goal of the proposed method is to provide a feature extraction method that is not sensitive to noise, lighting conditions and rotation angles. Analysis of the proposed HCLBP was done with the existing LBP and CLBP methods.

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2. METHODOLOGY

2.1. Local Binary Pattern

Local binary pattern (LBP) proposed by Ojala et al [13] is a considered to be a successful method of examining textures. LBP describes the spatial structure of the local image texture. LBP operator characterize the pixels by thresholding the neighborhood of each pixel with the center pixel value and a binary number is obtained. LBP is computed by the Equations (1 and 2).

$$LBP_{P,R} = \sum_{P=0}^{P-1} S\left(g_p - g_c\right) 2^P \tag{1}$$

$$s\left(x\right) = \left(1, x \geq 0; 0, otherwise\right) \tag{2}$$

where g_c is the gray value of the central pixel, g_p is the value of its neighbors, P is the total number of involved neighbors and R is the radius of the neighborhood. A local binary pattern is called uniform if the binary pattern obtained has a maximum of two bitwise transitions from 0 to 1 or vice versa when the bit pattern is traversed circularly.

The rotation invariant pattern of LBP, LBP^{riu2} is defined in Equation 3.

$$LB\mathrm{P}_{P,R}{}^{riu2} = \left(\sum_{p=0}^{P-1} s\left(g_p - g_c\right) ifU\left(LBP_{P,R}\right) \leq 2; P+1, otherwise \right) \tag{3}$$

LBP variance (LBPV) provides joint LBP and contrast distribution where the variance $VAR_{P,R}$ is used as an adaptive weight to adjust the contribution of the LBP code in histogram calculation.

$$VAR_{P,R} = \frac{1}{P} \sum_{p=0}^{P-1} \left(g_p - \mu\right)^2 \tag{4}$$

Where

$$g(x,y) = \mu = \frac{1}{P} \sum_{p=0}^{P-1} g_p \tag{5}$$

The drawbacks of the LBP is that the local binary pattern computed for images with and without noise is different but for images with different gray levels the local binary pattern obtained is the same. The image gray levels change with illumination and therefore a new feature extraction method proposed here pays attention to the noise present in the image in the real environmental condition.

2.2. Homomorphic based Completed Local Binary Pattern

To reduce the drawbacks of LBP, a feature extraction method for texture classification has been proposed in this paper based on completed local binary pattern. Images acquired under poor illumination and noisy environment yield an undesired condition in computer vision based systems. In the proposed method the noise present in the image is first removed, then the changes in the image due to poor illumination is withdrawn from the image. Finally the histogram features for the texture images that are to be classified is obtained using completed local binary pattern.

Averaging operation plays a vital role in low level image processing like texture analysis. It is one of the building blocks for the complex feature extraction operators. Taking into consideration the importance of local and global features in an image, in our work in the first stage the texture images are pre-processed to preserve the mean, whereby smaller scales are attenuated rather than coarser scales. The pre-processing here involves choosing a filter with zero shifting property where the filter mask and its transfer function are isotropic. The box filter is chosen to have high computation efficiency. We consider $g(x, y)$ as the texture image obtained after pre-processing the image $f(x, y)$.

In the second stage, the illuminance component and reflectance component of the image $g(x, y)$ under different lighting conditions are considered, and therefore a homomorphic filter with the Gaussian high pass filter is used. Homomorphic filtering of the image involves logarithmic operation, fourier transform, filtering operation, inverse fourier transform and exponentiation operations. Equations (6-9) gives the operations performed in the image.

$$g(x,y) = i(x,y)\,r(x,y) \tag{6}$$

$i(x, y)$ is defined as the illuminance component and $r(x, y)$ is the reflectance component of the

image $g(x, y)$

$$z(x,y) = \ln\left(i(x,y)\,r(x,y)\right) \tag{7}$$

$$S(U,V) = H(U,V)\,Z(U,V) \tag{8}$$

$Z(U, V)$ is the fourier transform of $z(x, y)$, $H(U, V)$ is the transfer function of the Gaussian high pass filter used in the process.

$$s(x,y) = F^{-1}\left(S(U,V)\right) \tag{9}$$

The changes produced in the image because of variations in illumination is reduced in the second stage of the proposed method. In the third stage the homomorphic filtered images obtained by the exponentiation of $s(x, y)$ is represented as the centre gray value and the local difference using completed local binary pattern. The local difference component is separated as sign (S) and magnitude (M) component. The proposed method is addressed here as HCLBP. In HCLBP the centre, sign and the magnitude components are coded as in CLBP [17] to obtain HCLBP_C, HCLBP_S, HCLBP_M. The histogram of the components are combined to obtain HCLBP_M/C, HCLBP_S_M/C, HCLBP_S/M and HCLBP_S/M/C. The chi square statistics is used to find the dissimilarity between the histograms of the images used for training and testing. The nearest neighbour is used as the classifier to calculate the classification accuracy using LBP, CLBP and HCLBP as feature extraction methods.

3. IMAGE DATA AND EXPERIMENTAL SETUP

Variations in the gray levels of an image change with illumination. Therefore texture images from Test suites Outex_TC_00010 and Outex_TC_00012 of the outex database [19] is used for the experimental evaluation of texture analysis algorithms used. Each texture is captured using three different simulated illuminants denoted as horizon, inca, and tl84. Each texture is captured using six spatial resolutions (100, 120, 300, 360, 500, and 600 dpi) and nine rotation angles (0^o, 5^o, 10^o, 15^o, 30^o, 45^o, 60^o, 75^o and 90^o). For TC_00010, samples of illuminant "inca" and angle 0^o in each class is used for classifier training and the other 8 rotation angles with the same illuminant is used for testing. For TC_00012, samples of TC_00010 with illuminant inca was used for training and all samples captured using illuminant tl84 and horizon is used for testing. Samples of the texture images is shown in Figure 1.The sample consists of textures from 24 different classes.

To analyze the texture analysis methods, experiment was conducted using LBP^{riu2}, LBPV, CLBP_S, CLBP_M, CLBP_M/C, CLBP_S_M/C, CLBP_S/M, CLBP_S/M/C, HCLBP_S, HCLBP_M,

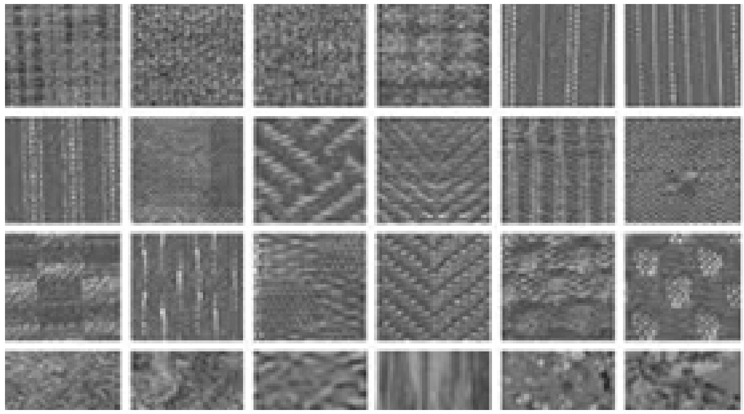

Figure 1: Samples of the 24 textures from Outex database

HCLBP_M/C, HCLBP_S_M/C, HCLBP_S/M and HCLBP_S/M/C for radius 1, 2 and 3 with 8,16 and 24 neighbors respectively. The high frequency gain and the low frequency gain of the Gaussian high pass filter was varied and was chosen to be 1.1 and 0.8 respectively to get a high classification accuracy.

4. RESULTS AND DISCUSSION

The performance result was obtained using the histogram features obtained for LBP^{riu2}, LBPV, CLBP_S, CLBP_M, CLBP_M/C, CLBP_S_M/C, CLBP_S/M, CLBP_S/M/C, HCLBP_S, HCLBP_M, HCLBP_M/C, HCLBP_S_M/C, HCLBP_S/M and HCLBP_S/M/C. The experiment result was obtained for the outex test suites TC_00010, TC_00012 (tl84) and TC_00012 (horizon) for different radius (R = 1, 2, 3) and different neighbours (P = 8, 16, 24). Results are obtained as the average of the accuracy obtained by repeating the experiment 10 number of times.

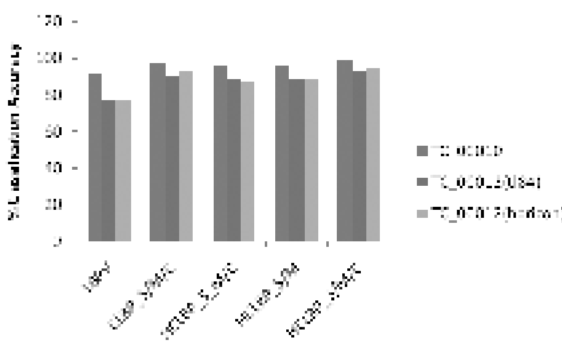

Figure 2: Classification result for the test suites radius 1 and 8 neighbours.

Figure 2.shows the classification accuracy obtained for LBPV, CLBP_S/M/C, HCLBP_S_M/C, HCLBP_S/M, HCLBP_S/M/C for test suites TC_00010, TC_00012(tl84) and TC_00012(horizon) with radius R=1 and neighbours P=8. From Fig 2. it is clear that highest accuracy is obtained for test suite TC_00010 and TC_00012 using the proposed method with the combined features.

Table I gives the result obtained for the methods considered for the analysis for radius (R) 1, 2 and 3 and neighbours (P) 8, 16 and 24 respectively. From table it is found that when the the illuminance and reflectance components are considered after preserving the small scale features the sign, magnitude components and the centre pixels separately and after combinations also produce better accuracy when compared with the existing methods.

Table 1
Comparison of the mean classification accuracy for LBPriu, LBPV, CLBP and HCLBP on test suites Outex_TC_00010, Outex_TC_00012 (tl84) and Outex_TC_00012 (horizon) for different radius R and neighbors P.

	TC_00010			TC_00012(tl84)			TC_00012(horizon)		
	R=1, P=8	R=2, P=16	R=3, P=24	R=1, P=8	R=2, P=16	R=3, P=24	R=1, P=8	R=2, P=16	R=3, P=24
LBP^{riu2}	84.8958	89.2448	91.562	65.3009	82.2917	85.0463	63.75	75.1389	80.8102
LBPV	91.5625	92.1615	93.372	76.6204	87.2222	91.3194	77.0139	84.8611	85.0463
CLBP_S	84.8177	89.4010	95.0281	65.46	82.2685	85.0463	63.6806	75.2083	80.7870
CLBP_M	81.7448	93.6719	95.5208	59.3056	73.7963	81.1806	62.7778	72.4074	78.6574
CLBP_M/C	90.3646	97.4479	98.0208	72.384	86.9444	90.7407	76.6667	90.9722	90.6944
CLBP_S_M/C	94.5313	98.0208	98.3333	81.875	90.995	82.7546	82.5231	91.0880	92.4074
CLBP_S/M	94.6615	97.8906	99.3229	82.7546	90.555	93.588	83.1481	81.1111	93.3565
CLBP_S/M/C	96.5625	98.7240	99.9323	90.3009	93.5417	95.3241	92.6917	93.9120	94.5370
HCLBP_S	86.5104	93.1771	93.6198	66.3657	88.0324	86.4213	61.3472	87.5046	83.75
HCLBP_M	89.6875	94.2448	97.0708	69.2130	78.2639	80.7250	68.9120	82.2500	82.4537
HCLBP_M/C	94.9219	97.6823	98.750	87.3241	90.5370	91.8333	86.9907	92.8287	93.7315
HCLBP_S_M/C	96.3802	98.4372	99.0163	88.7356	94.1715	95.4213	87.5231	94.3565	95.7454
HCLBP_S/M	96.4844	98.7760	99.6010	88.9437	94.4537	95.6765	88.2313	94.7769	95.2130
HCLBP_S/M/C	97.9688	98.9583	99.7573	93.6389	97.0417	98.8981	94.6574	97.8056	98.6898

5. CONCLUSION

Analysis using Homomorphic based completed local binary pattern HCLBP as the feature extraction showed better immunity to noise and invariance to illumination and rotation angle changes when compared with LBP and CLBP for the test suites TC_00010, TC_00012(tl84) and TC_00012(horizon). Therefore it is clear that pre-processing of the images are done using box and homomorphic filters, yield a higher performance result .The proposed method can be analyzed by replacing the Gaussian filter used in the Homomorhic filtering with adaptive filters. The maximum accuracy for the proposed method is obtained for radius 3 with 24 neighbors at the cost of increased computation time. New algorithms can be developed to reduce the computation time without reduction in the classification accuracy. In future the texture analysis can be done on texture images from Brodatz and Vistex database.

References

[1] Chen C. H., Pau L. F., Wang P S P (eds.), The Handbook of Pattern Recognition and Computer Vision (2nd Edition). World Scientific Publishing Co. 1998; pp. 207-248.

[2] Liu F., Picard R. W., Periodicity, Directionality and randomness: Wold features for image modeling and retrieval. IEEE Trans. Pattern Analysis and Machine Intelligence. 1996 Jul; 18, (7), pp. 722–733.

[3] Randen T, Husoy J H, Filtering for Texture Classification: A Comparative Study. IEEE Trans. Pattern Analysis and Machine Intelligence. 1999; 21, pp. 291-310,

[4.] Haralick R. M., Shanmugam K., Dinstein I., Textural Features for Image Classification. IEEE Trans. Systems, Man, and Cybernetics. 1973 Nov; 3(6), pp. 610-621.

[5] Weszka J. S., Dyer C. R., Rosenfeld A., A Comparative Study of Texture Measures for Terrain Classification. IEEE Trans.Systems, Man, and Cybernetics. 1976 Apr; 6 (4), pp. 269-285.

[6] Cross G. R., Jain A. K., Markov Random Field Texture Models. IEEE Trans. Pattern Analysis and Machine Intelligence. 1983 Jan; 5(1), pp. 25-39.

[7] Zhu S. C., Wu Y., Mumfors D., Markov Random Field Texture Models. International Journal on Computer Vision. 1998; 27(2), pp. 107-126.

[8] Mao J. and Jain A. K., Texture Classification and Segmentation Using Multiresolution Simultaneous Autoregressive Models. Pattern Recognition. 1992; 25(2), pp. 173-188.

[9] Kaplan L. M., Extend Fractal Analysis for Texture Classification and Segmentation. IEEE Trans. Image Processing. 1999 Nov; 8(11), pp. 1572-1585.

[10] Leung T., Malik J., Representing and recognizing the visual appearance of materials using three-dimensional textons. International Journal of Computer Vision. 2001; 43(1), pp. 29-44.

[11] Cordelia S., Constructing models for content-based image retrieval. Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. CVPR 2001, pp. 39-45, doi:10.1109/CVPR.2001.

[12] Varma M., Zisserman A., A statistical approach to texture classification from single images. International Journal of Computer Vision. 2005; 62(1), pp. 61-81.

[13] Ojala T., Pietikainen M., Maenpaa T., Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. IEEE Transactions on Pattern Analysis and Machine Intelligence. 2002; 24, pp. 971-987.

[14] Shu L., Law M., Chhung A Dominant local binary patterns for texture classification.IEEE Trans Image Processing .2009; 18(5):1107-1118.

[15] Guo Z., Lei Z., Zhang D., Rotation invariant texture classification using LBP variance (LBPV) with global matching. Pattern Recognition. 2010; 43(3), pp. 706-719.

[16] Zhenhua G., Lei Z., Zhang D., Su Z., Rotation invariant texture classification using adaptive LBP with directional statistical features. Proceedings of the International Conference on Image Processing. ICIP 2010, September 26-29, Hong Kong, China. IEEE 2010; pp. 285-288.

[17] Zhenhua G., Lei Z., Zhang D., A completed modeling of local binary pattern operator for texture classification. IEEE Transactions on Image Processing. 2010; 19(6), pp. 1657-1663.

[18] Yang Z., Wei J., Rong X. H., Hai M., Completed robust local binary pattern for texture classification, Neurocomputing. 2013; 106, Pages 68-76.

[19] Ojala T., Maenpaa T., Pietikainen M., Viertola J., Kyllonen J., Huovinen S., Outex-New framework for empirical evaluation of texture analysis algorithms .in Proc.16th International Conference on Pattern Recognition. 2002; 1, pp. 701-706.