TEXTURE IMAGE DELEGATION BY SSLBP

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Abstract - *The local binary pattern (LBP) has been used successfully in pattern recognition and computer vision applications, such as texture recognition. It could effectively address grayscale and rotation variation. However, it did not achieve the desirable performance for the classification of the texture with the transformation of the scale. In this paper we propose a new method based on LBP dominant in the scale space to address the variation of scale for texture classification. First, a scale space of a texture image is derived from a Gaussian filter. Then, a histogram of preschool LBPs is constructed. The local binary pattern (LBP) has been successfully used in pattern recognition and computer vision applications, such as texture recognition. It could effectively address grayscale and rotation variation. Without the embargo, it did not achieve the desirable performance for the classification of the texture with the transformation of the scale. In this paper we propose a new method based on LBP dominant in the scale space to address the variation of scale for texture classification. First, a scale space of a texture image is derived from a Gaussian filter. Then, a histogram of dominant preschool LBPs is constructed for each image in the scale space. Finally, for each pattern, the maximum frequency between different scales is considered as the invariable characteristic of scale.*

Keywords—**Local binary pattern, scale selective, texture classification, nearest subspace classifier.**

1. INTRODUCTION

Texture classification is a subject of active research in the fields of computer vision and pattern recognition. It has a wide range of applications, such as tissue inspection [2], remote sensing [3], and medical imaging analysis [4]. Early texture classification methods focus on the statistical analysis of texture images. Representative methods include the co-occurrence matrix [5] and methods based on filtering [6]. Since images can be captured under different lighting conditions and pose, a good texture classification should address gray scale, rotation and scale variations. In the first stage, many models were scanned to obtain rotation and gray scale invariant texture classification, such as autoregressive model [7], multi-resolution [8], hidden Markov model [9] and Gauss Markov random field [10].

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Texture recognition is an important area of computer vision research and pattern recognition [12]. It finds numerous applications in the industry such as surface inspection, remote sensing, categorization of materials. A number of approaches to texture classification have been proposed over the years. The above methods were based on filter banks, co-occurrence statistics and hidden Markov models.

2. RELATED WORKS

This chapter gives an overview of different texture classification methods and existing systems. The representative methods of statistical representation, to name a few, include co-occurrence matrices, Markov random fields, local binary pattern (LBP) and its extensions, texton dictionary-based methods and Weber local descriptor (WLD). Among these methods, LBP-based and texton dictionary based methods have the similar procedures which can be concluded in three steps. First, the neighbourhood property or responses of filter bank are used to generate local feature vectors for describing local structures of an image (every pixel corresponds to a local feature vector).

Secondly, each local entity vector is transformed into a unique code number by vector quantization (this step could be treated as the local feature space partition). Finally, the frequency histogram of code numbers is used to form the corresponding image rendering characteristic. The LBP approach works quickly due to its simple operation and has achieved impressive classification results in representative texture databases. Although the LBP method is very successful, there are still some problems.

LBP-based methods have achieved impressive classification results in representative texture databases and LBP has been deployed in many other applications, such as facial recognition, dynamic texture recognition and shape localization. And many variants of LBP, including dominant LBP (DLBP), derived-based LBP, center-symmetric LBP and terminated LBP (CLBP), have recently been proposed. But these methods could not address the issue of scale variation. Here proposed to find an optimal scale for each pixel and extract the LBP feature with the optimal scale. However, it could not extract coherent and accurate scale for all pixels. Overall fractal feature are not robust when the image size is small. To our best knowledge, the LBP function alone could not obtain good performance for database texture with significant scale variation, such as UIUC [13] and ALOT texture databases.

3. COMPLETE LOCAL BINARY PATTERN (CLBP)

The proposed method uses CLBP to extract scale sensitive features first, and then applies a scale selective scheme to get SSLBP. Thus, the fundamental CLBP is briefly introduced. CLBP is a gray-scale texture operator that characterizes the local spatial structure of the image texture. Referring to Fig1, given a central pixel gc and its P circularly and evenly spaced neighbours gp with radius R, $p = 0, 1, \ldots, P-1$, it can simply calculate the difference between gc and gp as $dp = gp - gc$. dp can be further decomposed into two components:

$$dp = \begin{cases} sp \times mp \end{cases} \quad (3.1)$$

$$sp = sign(dp) \text{ and } \quad mp = |d\,p| \quad (3.2)$$

where, $$sp = \begin{cases} 1, & dp \geq 0 \\ -1, & dp < 0 \end{cases} \quad (3.3)$$

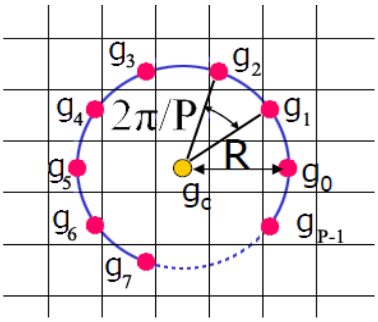

Fig-3.1: Central pixel and its P circularly and evenly spaced neighbours with radius R.

Sp is the sign and mp is the magnitude of dp. From the previous analysis, see that dp can be approximated more accurately using the component of sign sp that the component of magnitude mp. This implies that sp will retain more information from dp than mp, and therefore is more likely to result in better pattern recognition performance. Where the classification of texture using the characteristics of the sign achieves a much greater precision than using the characteristics of magnitude. The local difference is decomposed into the sign (S) and magnitude (M) components by the LDSMT.

Both CLBP_S and CLBP_M produce binary strings for them to be. There are two ways to combine the CLBP_S and CLBP_M codes: in concatenation or jointly. In the first form, we calculate the histograms of the CLBP_S and CLBP_M codes separately and then concatenate the two histograms together. This CLBP scheme can be represented as "CLBP_S_M". In the second form, compute a 2-D set histogram of the CLBP_S and CLBP_M codes. This CLBP scheme is represented as "CLBP_S / M". The central pixel, which expresses the local gray level of the image, also has discriminant information. The three operators, CLBP_S, CLBP_M and CLBP_C, could be combined in two ways, joint or hybrid. In the first way, similar to the histogram of the 2-D joint, we can construct a 3-D articular histogram of them, degraded by "CLBP_S / M / C".

In the second form, a 2-D joint histogram, "CLBP_S / C" or "CLBP_M / C" is first constructed, and then converted to a 1-D histogram, which is concatenated with CLBP_M or CLBP_S to generate a joint histogram, Designated by "CLBP_M_S / C" or "CLBP_S_M / C". Completed LBP (CLBP) to retain more structure information as well. The CLBP contains three operators, CLBP_Center, CLBP_Sign, and CLBP_Magnitude, which are defined to extract the local gray level of the image, sign, and vectors of local magnitude characteristics respectively. The process of constructing LBP features is independent of the data, since the representation of each image is not based on the training images.

4. SCALE INVARIANT FEATURE EXTRACTION AND MATCHING

4.1. Feature Extraction Scheme

The dominant local statistical patterns provide much of the discriminating information for the classification of the texture. When an image is enlarged or decreased, a dominant pattern still exists, but it will occupy a larger or smaller image region. In other words, the percentage of this pattern in the image does not change, but its characteristic scale does. Thus, you can find your characteristic scale and extract your percentage to that scale, you could achieve scale invariance. Based on this assumption, in this study, we designed a scheme of extraction of invariant characteristics of simple and novel scale for LBP finding dominant patterns of scale spaces.

The dominant local statistical patterns make much of the discriminating information for the classification of the texture. A training stage is applied to find dominant patterns by analyzing the scale space of a training set. First, given a training sample, a scale space is derived by a 2D Gaussian filter. Then, for each image in the scale space, a local pattern histogram is constructed. For each pattern, the maximum frequency between different scales is maintained to construct a new histogram. This histogram is used as a scale invariant characteristic for the given training sample. Finally, some dominant patterns with average high frequency are selected throughout the training set. Our method extracts frequency information from learned and fixed patterns, so the type of pattern containing important information is maintained.

➢ **Algorithm 1: Feature Learning**

Input: The training image set, *T= {fi | i=1,2…,N }*, fi is a training image and N is the size of the training set. *K* is the number of dominant pattern to be learned for *CLBP_S/C.L* is the of the scale space for a given image. $g\sigma$ is the 2D Guassian filter with a standard deviation σ to built the scale space.

Output: K dominant pattern for *CLBP_S/C*

Procedure:

Step 1: initialize one pattern histogram for training set, built a scale space by 2D Guassian filter:

$$Sl = \begin{cases} I & , \quad l = 1 \\ Si - 1 * g\sigma & , \quad 1 < l \leq L \end{cases}$$

Step 2: Compute local pattern histogram for each image.

Step 3: Only maximal frequency among different scale is kept $H^{fi} = CLBP\_S/C^{(K)} \max(H)$ $(H^{s1}CLBP\_S/C^{(K)}, H^{s2}CLBP\_S/C^{(K)}, \ldots, CLBP\_S/C^{(K)}$

Step 4: Compute average frequency for the whole training set;

$$H^T CLBP\_S/C^{(K)} = H^T CLBP\_S/C^{(K)} + H^{fi}\frac{CLBP_S/C^K}{N}$$

Step 5: Dominant pattern with high frequency are learned. Finding dominant patterns by analyzing the whole training set, the scale invariant.

4.2. Feature Matching

In this work two classes of classifiers are implemented. First, like traditional LBP methods, the NNC with the chi-square distance [27] is used to show the efficiency of the proposed scheme extraction scheme.

4.3. Classification

The k-NN Classifier is used for classification of textures. KNN is a simple algorithm that stores all available cases and classifies new cases based on a similarity measure.

4.4 Database

Here take UIUC data to check the efficiency of the work. The UIUCTex dataset contains 25 texture classes with 40 images per class. The textures are seen under significant changes of scale and point of view. In addition, the data set includes non-rigid deformations, lighting changes and appearance variations depending on the point of view. To evaluate the effectiveness of the proposed method, we perform here the UIUC database between a series of five large textures are acquired under significant scale and changes in point of view. Arbitrary rotation and uncontrolled illumination and commonly used texture Databass: UIUC [12],CUReT KTH-TIPS, UMD and ALOT. It has been designed to require local invarance.

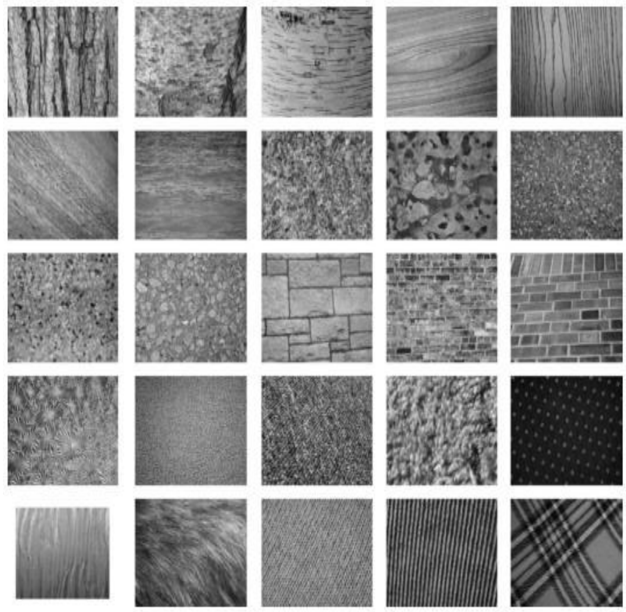

Fig-4.1: [1] UIUC Database.

5. RESULT AND ANALYSIS

The experimental results of the proposed technique for texture classification using SSLBP are discussed in this section. An application is created using MATLAB application to implement this technique.

5.1. Results

The algorithm discussed above is implemented using MATLAB R2013a. In the proposed method implemented by using many modules and sub modules. The input image is a texture image. Based on this input image extract the sign, magnitude, centre components are calculated then built the histogram. The histogram is considered as the scale selective features. First module is the feature extraction. Second module is the dataset training. Third module is classification and this can be done by Nearest Neighbour classifier. Figure 7.1 to 7.5 shows the result of various modules discussed above and shows representative results of texture classification.

5.2. Analysis

All entries are tested to find the accuracy of the work. The test input contains both trained and untrained images. When an untrained image is selected as input, the accuracy of the prediction is reduced. In the case of a trained image, the prediction accuracy is above 90%. The prediction chart is shown below. When selecting the untrained image as input, sometimes untrained images are classified into incorrect or different classes.

Fig-5.1: Input Image.

Fig-5.2: CLBP Sign.

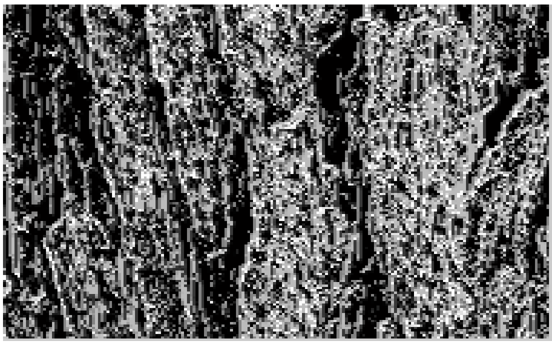

Fig-5.3: CLBP Magnitude.

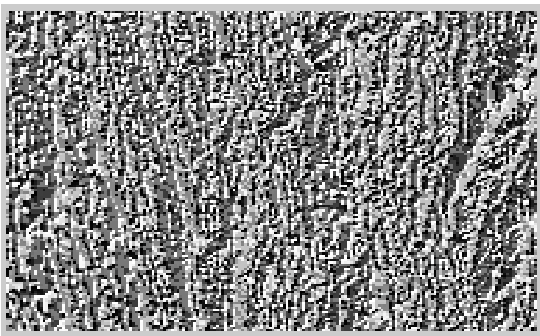

Fig-5.4: CLBP Centre.

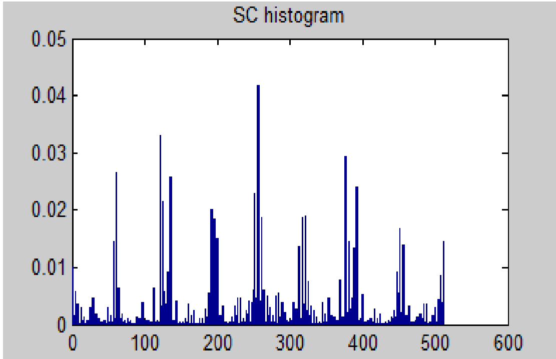

Fig-5.5: SC Histogram.

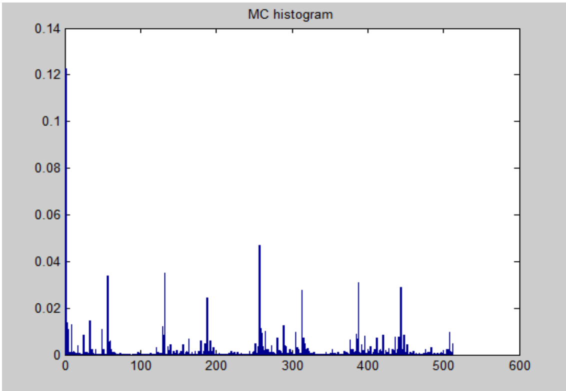

Fig-5.6: MC Histogram.

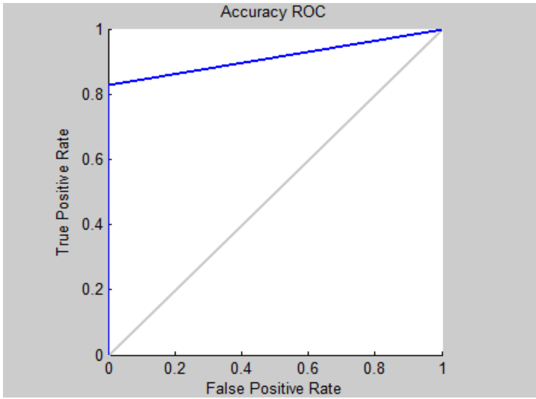

Fig-5.7: Accuracy Graph.

6. CONCLUSION

In this study, proposed a novel and simple scale invariant texture classification: scale invariance is achieved by analysing the scale space of LBPs. It demonstrated that the proposed method could get very promising results on five public texture databases. The proposed method is fast lies in enough for many real time applications. The main contribution of this study two aspects. First, LBP is a simple but efficient operator to address rotation and gray-scale invariance.

The local binary pattern (LBP) has been used successfully in pattern recognition and computer vision applications, such as texture recognition. It could effectively address grayscale and rotation variation. However, it did not achieve the desirable performance for texture classification with scale transformation. We propose a new method based on LBP dominant in the scale space to address the variation of scale for texture classification. First, a scale space of a texture image is derived from a Gaussian filter. Then, a histogram of dominant Preschool LBPs is constructed for each image in the scale space. Texture image is derived from a Gaussian filter. Then, a histogram of dominant Preschool LBPs is constructed for each image in the scale space. Finally, for each pattern, the maximum frequency between different scales is considered as the scale invariant characteristic. Extensive experiments in public texture databases (University of Illinois at Urbana-Champaign) validate the efficiency of the proposed feature extraction scheme. Together with the closest classifier, the proposed method could yield competitive results, which are 86.972% for UIUC.

REFERENCE

[1] Zhenhua Guo, Member, IEEE, Xingzheng Wang, Jie Zhou, Senior Member, IEEE, and Jane You, Member, IEEE " Robust Texture Image Representation by Scale Selective Local Binary Patterns," IEEE transactions on image processing, vol. 25, no. 2, february 2016.

[2] F. S. Cohen, Z. Fan, and S. Attali, "Automated inspection of textile fabrics using textural models," IEEE Trans. Pattern Anal. Mach. Intell., vol. 13, no. 8, pp. 803–808, Aug. 1991.

[3] H. Anys and D.-C. He, "Evaluation of textural and multipolarization radar features for crop classification," IEEE Trans. Geosci. Remote Sens., vol. 33, no. 5, pp. 1170–1181, Sep. 1995.

[4] Q. Ji, J. Engel, and E. Craine, "Texture analysis for classification of cervix lesions," IEEE Trans. Med. Image., vol. 19, no. 11, pp. 1144–1149, Nov. 2000.

[5] R. M. Haralick, K. Shanmugam, and I. Dinstein, "Textural features for image classification," IEEE Trans. Syst., Man, Cybern., vol. SMC-3, no. 6, pp. 610–621, Nov. 1973.

[6] T. Randen and J. H. Husoy, "Filtering for texture classification: A comparative study," IEEE Trans. Pattern Anal. Mach. Intell., vol. 21, no. 4, pp. 291–310, Apr. 1999.

[7] R. L. Kashyap and A. Khotanzad, "A model-based method for rotation invariant texture classification," IEEE Trans. Pattern Anal. Mach. Intell., vol. PAMI-8, no. 4, pp. 472–481, Jul. 1986.

[8] J. Mao and A. K. Jain, "Texture classification and segmentation using multi resolution simultaneous autoregressive models," Pattern Recognit., vol. 25, no. 2, pp. 173–188, 1992.

[9] J.-L. Chen and A. Kundu, "Rotation and gray scale transform invariant texture identification using wavelet decomposition and hidden Markov model," IEEE Trans. Pattern Anal. Mach. Intell., vol. 16, no. 2, pp. 208–214, Feb. 1994.

[10] H. Deng and D. A. Clausi, "Gaussian MRF rotation-invariant features for image classification," IEEE Trans. Pattern Anal. Mach. Intell., vol. 26, no. 7, pp. 951–955, Jul. 2004.

[11] Jing Yi Tou, Yong Haur Tay, Phooi Yee Lau "A Comparative Study for Texture Classification Techniques on Wood Species Recognition Problem", 2009 Fifth International Conference on Natural Computation.

[12] M. Varma and R. Garg, "Locally invariant fractal features for statistical texture classification," in Proc. IEEE 11th Int. Conf. Comput. Vis., Oct. 2007, pp. 1–8.