Rotation Invariant Static And Dynamic Texture Classification With Local Binary Count (LBC)

ABSTRACT

Texture classification is one of the four problem domains in the field of texture analysis. Local Binary Count (LBC) is a static local descriptor that can enhance the performance of rotation invariant texture classification. It extracts the local binary grayscale difference information and abandons the microstructure information. A variant of LBC named Completed LBC (CLBC) is used for static texture classification. It has two additional operators namely magnitude and centre along with LBC. For dynamic textures, two descriptors have been proposed namely Volume LBC (VLBC) and LBC-TOP (LBC from Three Orthogonal Planes). Experiments were conducted using OUTEX database for Static texture classification and DYNTEX database for Dynamic texture classification. The experimental results show that proposed descriptors can provide better classification accuracy with reduced computational complexity and time and also effectively deal with rotation variations of dynamic textures than the earlier approaches based on Local Binary Pattern (LBP).

Keywords:LBC,completedLBC,VLBC,LBC-TOP,χ2statistics

1. INTRODUCTION

Texture analysis is a basic vision problem, with application in many areas, e.g., object recognition, remote sensing and content-based image retrieval. Texture analysis can be divided into four problem domains as follow: texture classification, texture segmentation, texture synthesis and shape from 3D.

The main goal of texture classification is to assign an unknown sample texture into a set of known texture classes. In many practical applications, textures are captured in arbitrary orientations and scale. So far, many approaches have been proposed to achieve rotation invariance for texture classification. In statistical methods, texture is generally described by the statistics of selected features, e.g., invariant histogram, texture elements and micro-structures. These include early approaches such as Co- occurrence matrices, Fourier descriptors, descriptors based on Hough transform. In model based methods, texture is usually presented as a probability model or a linear combination of a set of basic functions. It includes autoregressive model, hidden Markov model, four tap wavelet filter coefficients. But they are not robust to variance in illumination.

In [1], Ojala et al proposed an efficient method, namely Local Binary Pattern (LBP), for rotation invariant texture classification. The algorithm of LBP contains two main steps, i.e., thresholding step and encoding step. In the thresholding step, the values of neighbor pixels are turned to binary values (0 or 1) by comparing them with the central pixel. Obviously, the local binary grayscale difference information is extracted in the thresholding step. In the encoding step, the binary numbers are encoded to characterize a structural pattern, and then the code is transformed into decimal number. Aiming at achieving rotation invariance, Ojala proposed rotation invariant uniform LBP (LBP^{riu2}), in which only rotation invariant uniform local binary patterns were selected. It was believed that LBP is an excellent measure of the spatial structure of local image texture since it can effectively detect micro-structures (e.g., edges, lines, spots) information. After that, a lot of variants of the LBP for rotation invariant texture classification have been proposed. For example, Heikkila et al [2] proposed center-symmetric LBP (CS-LBP) by comparing center-symmetric pairs of pixels instead of comparing neighbors with central pixels. Liao et al [3] presented Dominant LBP (DLBP), in which dominant patterns were experimentally chosen from all rotation invariant patterns. Others tried to further explore the contrast information. For example, Tan and Triggs [4] proposed the method of Local Ternary Pattern (LTP), which extends original LBP to 3-valued codes. Guo et al [5] proposed the completed LBP (CLBP) by combining the conventional LBP with the measures of local intensity difference and central gray level. LBP encoding process is used in all of these variants mentioned above because it is believed that structural patterns characterized by the binary codes are more important for rotation invariant texture recognition while local binary grayscale difference information is considered to be merely a supplement of micro-structures. Experimental results illustrate that the most discriminative information of local texture for rotation invariant texture classification is not the 'micro-structures' information but the local binary grayscale difference information. Thus it can be eliminated by using a local operator that discards the structural information from LBP operator, which is known as Local Binary Count (LBC). A completed LBC (CLBC) similar to CLBP can achieve comparable accurate classification rates. In addition, CLBC allows slight computational savings in the process of training and classification.

The rest of this paper is organized as follows: Section II presents the static texture descriptors. Section III presents the proposed dynamic texture descriptors. Section VI

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describes the classifier. Experimental results are presented in Section V and Section VI concludes the paper with some conclusive remarks.

II. STATIC TEXTURE DESCRIPTORS

A. Local Binary Count (LBC)

In the original LBP and its variants, each pixel in the local neighbor set is turned to binary form by comparing it with the central pixel. Then these binary values are encoded to form the local binary patterns. In the proposed LBC, we only count the number of value 1's in the binary neighbor sets instead of encoding them. The working principle of LBC is illustrated in Fig. 1. The number of value 1's is 4 in the binary neighbor set, thus the LBC code of the central pixel is also 4.

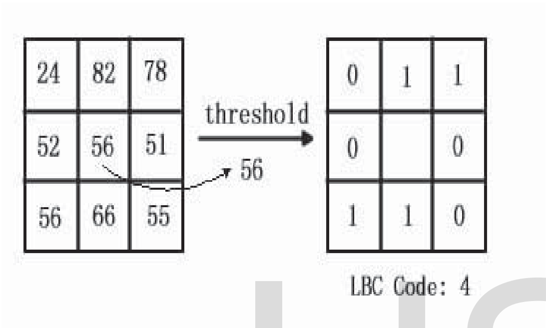

Fig.1. Illustration of LBC (P = 8, R = 1).

As a result, we can define the computing process for the LBC as follows:

$$LBC_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)\,, \qquad \text{——(1)}$$

$$\text{where,} \qquad s(x) = \begin{cases} 1, & x < 0 \\ 0, & x \geq 0 \end{cases}$$

where g_c represents the gray value of the center pixel and g_p (p= 0, 1, . . . ,P-1) denotes the gray value of the neighbor pixel on the circle of radius R and P denotes the total number of neighbors. The main difference between the LBP and the LBC is that the LBP is to use the binary number to encode local patterns while the LBC merely counts the number of value 1's in local neighbor set. But their meanings are very different. Usually, the LBP is to focus on the local structural information characterized by various patterns, while the LBC is only involved in the fact that how many pixels have comparatively higher gray level than the central one in local area. In other words, the LBP can extract the local structure information, while the LBC is merely to focus on the local binary grayscale difference information. Macroscopic textures can be regarded as the repeats for a large number of local microcosmic patterns. Thus, the statistics of the selected local microscopic patterns can characterize the whole texture. But the "micro-structure" is quite different from macroscopic textural structure.

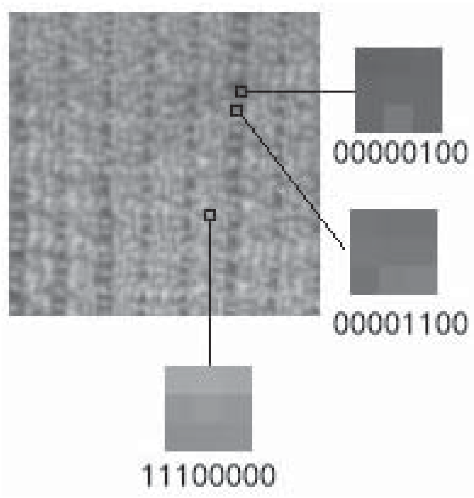

Fig. 2. Schematic diagram of macroscopic textural structure that is quite different from the micro- structure

As illustrated in Fig. 2, the micro-structures, "00000100" and "00001100" may be contained in a macroscopic "line" in texture image and a microstructure "line" (e.g., "11100000") may be a "spot" in the image. Thus, macroscopic textural structure can be characterized by the statistics of the micro-structures, but not the micro-structures themselves. These micro-structures do not represent the macroscopic textural structures directly. Although the LBC codes don't represent visual micro-structure, the LBC features can distinguish the different distributions of local pixels. Thus, the statistics of the LBC features can also be used to represent the macroscopic textural structures.

B. Completed Local Binary Count (CLBC)

Completed Local Binary Count (CLBC) can extract completed local textural information. It contains three operators:

- CLBC-Sign (*CLBC_S*),
- CLBC-Magnitude (*CLBC_M*) and
- CLBC-Center (*CLBC_C*).

Generally, the *CLBC_S* equals to the original LBC described above in Eqn. (1). In
order to code the *CLBC_M* in a consistent format with that of the *CLBC_S*, the *CLBC_M* can be defined as:

$$CLBC\_M_{P,R} = \sum_{p=0}^{P-1} s(m_p - c)\,, m_p = |g_p - g_c| \qquad \text{——(2)}$$

where g_p, g_c, and $s(x)$ are defined as in Eqn. (1) and c denotes the mean value of m_p in the whole image. The CLBC_M counts how many neighbors have comparatively much higher intensity than the center pixel. Thus it is used to extract additional information of the local intensity differences.

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In [5], it has been proven that the center pixel can be used to express the local gray level in the image. Thus the CLBC_C can be defined identical to the CLBP_C as follows:

$$CLBC\_C_{P,R} = s\,(g_c - c_I) \qquad (3)$$

where threshold c_I is set as the average gray value of the whole image. The different operators can be combined jointly and hybridly. In the first way, joint histograms (3D histograms) are taken and in the second way the 2D histograms are concatenated.

III. DYNAMIC TEXTURE DESCRIPTORS

A. Volume LBC (VLBC)

VLBC is computed from three frames of the video sequence: the current frame or the frame of the pixel for which the code is being computed and the previous and posterior neighbouring frames with time interval L.

B. LBC- TOP

The LBC is computed from three orthogonal planes i.e., XY, XT, YT planes. The histograms obtained are concatenated into a single histogram.

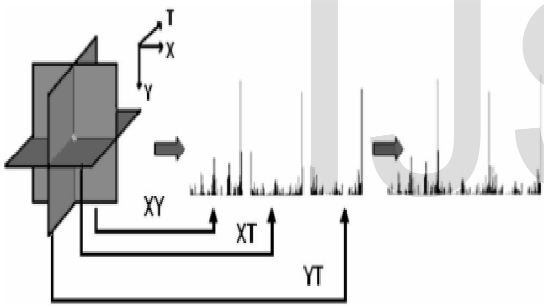

Fig. 3 Computation of LBC-TOP

VI. CLASSIFIER

A. Dissimilarity Measure - χ2 Statistics

In this paper, we utilized the χ2 statistics as the dissimilarity between two histograms. The χ2 statistics is a bin-by-bin distance, which means only the pairs of bins that have the same index are matched. If H = {hi} and K = {ki} (i = 1, 2…B) denote two histograms, then χ2 statistics can be calculated as follows:

$$d\chi2\,(H, K) = \sum_{i=1}^{B} \frac{(hi - ki)^2}{hi + ki} \qquad (4)$$

χ2 metric is computed for the histograms of the resultant test and train images or sequences. A simple multi-resolution framework can be used to improve the classification accuracy.

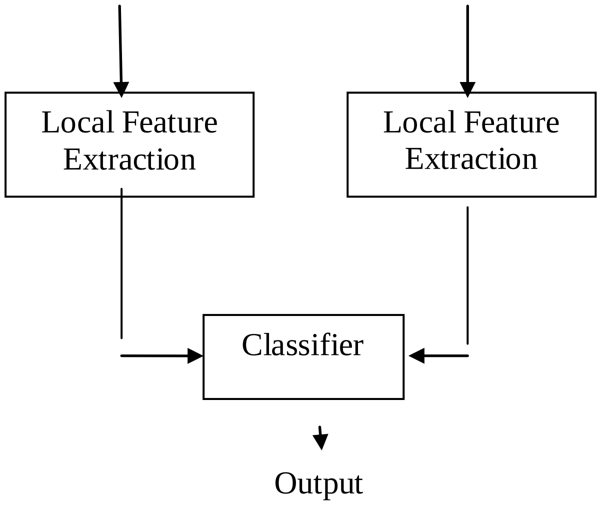

Fig. 4 General block diagram for Texture Classification

B. Nearest Neighbor Classifier

The nearest neighbor algorithms are simple classifiers that select the training samples with the closest distance to the query sample. These classifiers will compute the distance from the query sample to every training sample and select the best neighbor or neighbors with the shortest distance. The nearest neighbor algorithm is simple to be implemented. However the speed of computing distance will increase according to the number of training samples available.

C. Database

A database is needed for texture classification and an experimental setup consisting of training and test images must be created out of it. The output of the classifier is usually performance measurement parameters like classification rate. It is obvious that the final outcome of a texture classification experiment depends on numerous factors, both in terms of the possible built-in parameters in the texture description algorithm and the various choices in the experimental setup.

V. EXPERIMENTS AND DISCUSSIONS

Experiments can be carried on three large and representative databases for static texture classification: the Outex database [6], CUReT database [7] and UIUC database [8]. For static texture, we have carried out experiments on Outex database . We have used Dyntex database for dynamic texture classification.

A. Experimental setup for static texture classification

We used the Outex test suite Outex_TC_0010 (TC10) which contains 24 classes of texture images captured under three illuminations “inca” and nine rotation angles (0°, 5°, 10°, 15°, 30°, 45°, 60°, 75°, and 90°). There are twenty 128×128 images for each rotation angle. The 24 × 20 images of rotation angle 0° were adopted as the training data. The other 8 rotation angles were used for test. Firstly, the CLBC_S and the CLBP_S, the CLBC_M and the CLBP_m achieve similar accurate classification rates respectively. The results of CLBC_S, CLBC_M, CLBC_C operators are shown in the following figure.

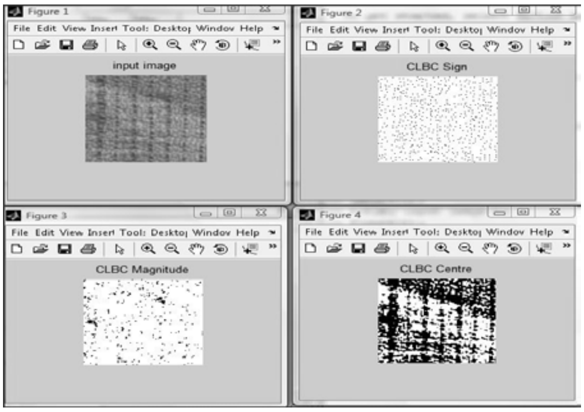

Fig. 4. From top left: Input image texture (Outex TC_00010), result of CLBC_S, CLBC_M, CLBC_C operators

Secondly, better classification rates than the ones obtained by LTP, LBP/VAR and DLBP can be achieved by combining 'Magnitude' with 'Sign' jointly or hybridly. In 2D-joint way, the CLBC_S_M and the CLBP_S_M can get similar classification rates. In the 3D-joint way, the CLBP_S/M/C and the CLBC_S/M/C achieve much better results than the other methods. The CLBP_S/M/C is slightly better than the CLBC_S/M/C. By applying the multi-scale scheme, some better results could be obtained. The following Table I lists the experimental results of different methods on TC10Database.

Classification Rate (%) for	P=8 R=1	P=16 R=1	P=8 R=2	P=16 R=2
CLBC_S	82.94	87.68	82.34	88.67
CLBC_M	78.95	84.42	84.92	92.44
CLBC_S_M/C	93.75	92.36	92.29	95.91
CLBC_M/C	89.50	95.98	96.30	96.92
CLBC_S/C	94.89	95.75	93.80	95.26
CLBC_M_S/C	95.26	96.53	96.48	97.57
CLBC_S_M	90.72	94.66	93.72	96.27
CLBC_S/M	95.23	96.77	98.09	98.09
CLBC_S/M/C	97.16	97.89	98.56	98.54

TABLE I:CLASSIFICATION RATES (%) ON TC10 DATASETS

B. Experimental setup for dynamic texture classification

Dyntex database is used for dynamic texture classification. The experimental setup used is a combination of the ones that were used in [9] and [10]. The setup in [10] cannot be used to evaluate the rotation invariance of the proposed descriptors. The new experimental setup is created using the new Dyntex database because the size of the DTs has been greatly reduced when compared to the original database. It is created from 18 videos belonging to seven classes (i.e., seas, calm water, fountains, vegetation, trees, flowers and traffic). The sequences were resized to 128 x 128 window size as used in static texture classification. Each sequence was divided into eight non overlapping subsets half in X, Y and T. The segmented sequences were rotated through four angles (0◦, 90◦, 180◦, 270◦). Thus a total of 576 (18 x 8 x 4) sequences were used as training samples. The sequences that were cut only in time direction were used as tests, accounting to 36 (18 x 2) test models

Classification rate (%) for	Classification Rate (%)
VLBC$_{1,8,1}$	91.6667
VLBC$_{2,8,1}$	90.2778
VLBC$_{1,4,1}$	92.0139
VLBC$_{2,4,1}$	88.3681
VLBC$_{1,2,1}$	76.2153
VLBC$_{2,2,1}$	72.7431
LBCTOP$_{8,8,8,1,1,1}$	79.5139
LBCTOP$_{8,8,8,3,3,1}$	77.7778
LBCTOP$_{16,8,8,1,1,1}$	81.7708

TABLE II: CLASSIFICATION RATES (%) ON DYNTEX DATABASE

VI. CONCLUSION

This paper presented two descriptors namely Volume LBC(VLBC) and LBC-TOP (LBC from three Orthogonal Planes) for dynamic texture and A variant of LBC named

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Completed LBC (CLBC) is used for static texture classification. The proposed variants of LBC can achieve comparable accurate classification rates with slight computational savings in the process of training and classification.

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