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An improved local binary pattern for texture classification

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ABSTRACT

This paper proposes an improved robust descriptor: the Joint Local Binary Patterns with Weber-like responses (JLBPW). The JLBPW descriptor mainly solves two problems of the existing Local Binary Pattern (LBP) method. The existing LBP methods discard the local intensity differences by holding their binary information. And the correlation of patterns under different scales is also ignored when the multi-resolution technique is used by the LBP methods. Aiming at the two problems, the JLBPW descriptor organizes the ignored local intensity differences according to the Weber's law that is discovered from psychological experiments. And the organized differences are set as responses of the corresponding joint patterns. The proposed descriptor supplies more information to describe local structures of images. Experiments on two representative databases demonstrate that the proposed descriptor is superior to other modern approaches.

1. Introduction

The texture classification as an important research topic has been paid much attention to during the past decades. In recent years, many approaches have been developed for texture analysis, including Local Binary Patterns (LBP) [1], Gabor wavelet [2,3], Radon transform [4] and texton learning [5,6]. Among these approaches, the LBP methods have been used more widely due to the high performance and effective computation. And it has been successfully applied to many computer fields, such as description of salient regions [7], face recognition [8] and so on. For texture classification, Ojala et al. [1] divide the local binary patterns into uniform patterns and non-uniform patterns according to the number of the 0/1 transitions in a pattern. And they propose a rotation-invariant uniform pattern (LBP^{riu2}) by merging the uniform patterns with the same number of '1' bits into a new pattern. Zhou et al. [9] make the best of the non-uniform patterns and introduce an extended local binary pattern (LBP^{exten}). Liao et al. [10] use the Dominant Local Binary Patterns (DLBP) to classify rotational textures, but the classifying process relies on the SVM classifier. Ahonen et al. [11] utilize the LBP Histogram Fourier features (LBP-HF) to classify rotation textures. Recently, Guo et al. [12] propose a more powerful LBP operator (CLBP) that combines three pieces of local information: local signs (CLBP_S), local magnitudes (CLBP_M) and center grays (CLBP_C).

In order to further improve the performance, the multi-resolution technique also employed by many LBP methods [1,9–12]. The multi-resolution technique extracts local binary patterns at different scales by altering the sampling parameters (the radius and the number of points) and concatenates the corresponding LBP histograms together to classify textures. The existing LBP methods with the multi-resolution technique compute the LBP histogram under one scale at a time. And they have not considered the relationship between patterns of a pixel under different scales. Another drawback of the existing LBP methods is the missing intensity information in a local region. The bit '0' in an LBP label expresses that the gray value of the central pixel is greater than the gray value of the corresponding neighboring pixel. However, there is missing information about how great their difference is. To solve the two problems, we employ the joint probability of local binary patterns under different scales to describe the texture image. And each pattern is assigned a response of the local difference. Jie et al. [13] use the Weber's law to compute the local differential excitation and divide the excitation into several segments. The numbers of pixels that fall into different segments and gradient orientations are reported to describe an image. Inspired by their work, we construct a Weber-like function to organize the local differences. We employ the organized differences as responses of the joint local

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binary patterns and propose a robust local descriptor: Joint Local Binary Patterns with Weber-like responses (JLBPW). And experimental results validate the effectiveness of the proposed method.

This paper is organized as follows. Section 2 introduces the basic local binary patterns and the proposed methods. In Section 3, the proposed method is evaluated on two public texture databases. Section 4 concludes the paper.

2. Joint Local Binary Patterns with Weber-like responses

2.1. Basic local binary patterns

The local binary pattern (LBP) [14] characterizes the local structure of the texture image in a small circularly symmetric neighborhood that has P equally spaced pixels on a circle of radius R. The values of the P pixels are assigned to 0 when their intensity values are lower than the center's and 1 otherwise. And the LBP label of the center pixel is obtained by summing the P binary values weighted with powers of 2:

$$\mathrm{LBP}_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p \tag{1}$$

$$s(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \tag{2}$$

where g_p is the gray value of the pth sampling point and g_c is the gray value of the central pixel. Ojala et al. [12] define the uniform patterns according to the number of 0/1 transition of the patterns. And they proposed the rotation-invariant uniform local binary pattern operator ($\mathrm{LBP}^{\mathrm{riu2}}$) for texture classification on the basis of the uniform patterns:

$$\mathrm{LBP}_{P,R}^{\mathrm{riu2}} = \begin{cases} \sum_{p=0}^{P-1} s(g_p - g_c), & \text{if } U(\mathrm{LBP}_{P,R}) \leq 2 \\ P+1, & \text{otherwise} \end{cases} \tag{3}$$

where

$$U(\mathrm{LBP}_{P,R}) = |s(g_{P-1} - g_c) - s(g_0 - g_c)| + \sum_{p=1}^{P-1} |s(g_p - g_c) - s(g_{p-1} - g_c)| \tag{4}$$

According to Eq. (3), there are $P+2$ output values in total. The histogram of LBP labels is computed to describe the texture. In order to enhance the performance, the multi-resolution technique is usually used. The multi-resolution technique concatenates the LBP histograms under different scales (P, R) together to compute the (dis)similarity between a model and a sample.

2.2. Joint local binary patterns

The LBP methods with the multi-resolution technique have shown good performances. Even so, the conventional LBP methods do not make the best of the patterns in different scales. These LBP methods have not considered the information among the patterns in different scales. The LBP methods in one scale just describe the simple structures of an image such as edge, spot, corner and so on. Here, we combine local binary patterns under different scales together to describe more structures of an image. Suppose the coordinates of a pixel are (x, y). The Joint Local Binary Pattern (JLBP) with two scales of the pixel (x, y) is defined as

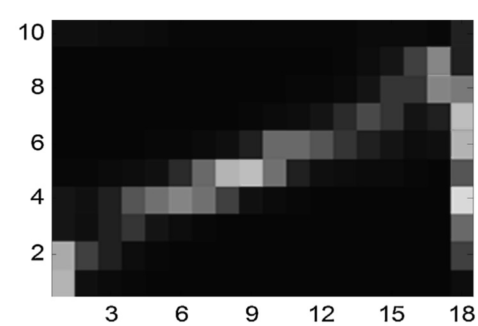
$$\mathrm{JLBP}_{S_1,S_2}(x, y) = (\mathrm{LBP}_{S_1}(x, y), \mathrm{LBP}_{S_2}(x, y)) \tag{5}$$

where $S_1 = (P_1, R_1)$ and $S_2 = (P_2, R_2)$ stand for two groups of different scale parameters (P, R). Similarly, the rotation-invariant uniform Joint Local Binary Pattern ($\mathrm{JLBP}^{\mathrm{riu2}}$) with two scales can also be defined as

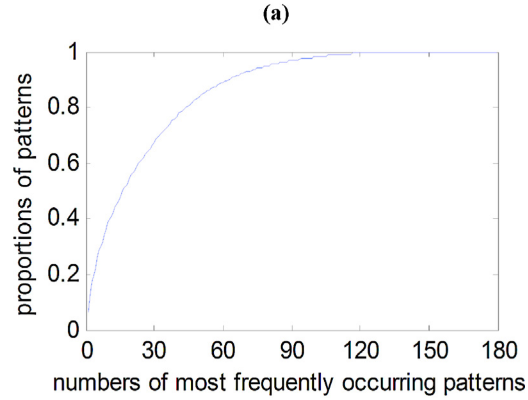
$$\mathrm{JLBP}_{S_1,S_2}^{\mathrm{riu2}}(x, y) = \left(\mathrm{LBP}_{S_1}^{\mathrm{riu2}}(x, y), \mathrm{LBP}_{S_2}^{\mathrm{riu2}}(x, y)\right) \tag{6}$$

The $\mathrm{JLBP}^{\mathrm{riu2}}$ with multi-scales can easily be extended by combining the different ${\mathrm{LBP}_{P,R}}^{\mathrm{riu2}}$ operators in the same way. The $\mathrm{JLBP}^{\mathrm{riu2}}$ label of a pixel is a multidimensional value. The number of the dimensionality depends on the number of selected scales (P, R). The JLBP is different from the existing LBP operators, because it reflects the relationships of the patterns under different scales. We execute the ${\mathrm{JLBP}_{(8,1),(16,2)}}^{\mathrm{riu2}}$ operator on 10,000 natural textures and compute the occurrence frequencies of the patterns. Fig. 1 presents the results. The sub-image (a) shows the correlation between the ${\mathrm{LBP}_{8,1}}^{\mathrm{riu2}}$ patterns and the ${\mathrm{LBP}_{16,2}}^{\mathrm{riu2}}$ patterns. All the occurrence frequencies of patterns are transformed into intensities in the sub-image (a). It is clear that some correlations of the patterns indeed exist. The occurrence frequencies of different $\mathrm{JLBP}^{\mathrm{riu2}}$ values are very different, because there is a potential relationship between the $\mathrm{LBP}^{\mathrm{riu2}}$ patterns under different scales. Considering a pixel with ${\mathrm{LBP}_{8,1}}^{\mathrm{riu2}} = 4$, there is a high probability that its ${\mathrm{LBP}_{16,2}}^{\mathrm{riu2}}$ value equals to 8, because the $\mathrm{JLBP}^{\mathrm{riu2}}$ pattern (4,8) represents the edge which is a frequent structure in an image. Other irregular structures can also be described, although they have lower occurrence probability.

The JLBP is very simple, but it has not been used to describe images. The major reason lies in the high dimension of the JLBP features. The $\mathrm{JLBP}^{\mathrm{riu2}}$ with three scales ((8,1), (16,2), (24,3)) has 4680 ($10 \times 18 \times 26$) patterns in total, while the corresponding $\mathrm{LBP}^{\mathrm{riu2}}$ only has 54 ($10+18+26$) patterns. More patterns lead to time-consuming calculation. In fact, some patterns of the $\mathrm{JLBP}^{\mathrm{riu2}}$ are



(a)



(b)

Fig. 1. The ${\mathrm{JLBP}_{(8,1),(16,2)}}^{\mathrm{riu2}}$ on 10,000 natural textures. (a) The average ${\mathrm{JLBP}_{(8,1),(16,2)}}^{\mathrm{riu2}}$ histogram of 10,000 natural textures. (b) The most frequently occurring ${\mathrm{JLBP}_{(8,1),(16,2)}}^{\mathrm{riu2}}$ patterns occupy proportions among all the patterns in the 10,000 natural texture images.