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Scale- and rotation-invariant texture description with improved local binary pattern features

Reza Davarzani, Saeed Mozaffari *, Khashayar Yaghmaie

Faculty of Electrical and Computer Engineering, Semnan University, Semnan, Iran

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A B S T R A C T

Local Binary Pattern (LBP) is an effective image descriptor based on joint distribution of signed gray level differences. Simplicity, discriminative power, computational efficiency and robustness to illumination changes are main properties of LBP. However, LBP is sensitive to scaling, rotation, viewpoint variations, and non-rigid deformations. In order to overcome these disadvantages of LBP, this paper proposes an improved LBP features. In our method, a circular neighboring radius and a dominant orientation are assigned to each pixel. To achieve scale invariance, we used the radius of blob-like structures to determine the circular neighboring set of each central pixel. Definition of LBP operator with respect to dominant orientation of each pixel can guarantee the rotation invariance of LBP features. Unlike original LBP operator which discards the magnitude information of the difference between the center and the neighbor gray values in a local neighborhood, a weighted LBP features is proposed in this paper. Several experiments are conducted to compare the proposed method with seven LBP-based descriptors for texture retrieval and classification using four databases: Brodatz, Outex, UIUC and UMD. Experimental results show that the proposed Weighted, Rotation- and Scale- Invariant Local Binary Pattern (WRSI_LBP) outperforms other LBP-based methods.

1. Introduction

Texture is the basic characteristic of many surfaces, objects, and scenes. Texture analysis is a well-known topic in image processing and computer vision and the fundament for many applications such as remote sensing, scene recognition, biomedical image analysis, image recognition and retrieval [1]. A large variety of algorithms for texture description already exists. But, rotation, spatial resolution, illumination, and viewpoint are still challenges in texture recognition. Texture analysis algorithms attempt to extract compact, distinctive, and efficient features to describe and differentiate several textures. They can be divided into four major categories [1]: structural methods, model based methods, signal processing methods and statistical methods.

In structural methods, a texture image is considered as a set of primitive texels in some regular or repeated pattern which are combined together by a predefined grammar. Since performance of structural techniques strongly relies on primitive detection, they are more suitable for artificial textures [2].

Model-based texture methods are based on constructing a parametric generative model captured from specific textures. Markov Random Fields [3], fractals [4], and multiresolution autoregressive features [5] are main model-based texture methods.

Signal processing methods, also called multichannel filtering methods, are based on spatial or frequency domain filtering. The filter response and high peaks in spectrum are used to describe textures. Randen et al. [6] presented a comparative study of filtering for texture classification.

* Corresponding author. Tel.: +98 9123023706.
E-mail addresses: mozaffari@semnan.ac.ir, saeed_mozaffari@yahoo.com (S. Mozaffari).

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Statistical approaches extract information from pixels positions and their values and yield characterizations of textures as smooth, coarse, grainy, and so on. Depending on the number of participated pixels, statistical methods can be further classified into three groups. First-order statistics only consider individual properties of pixels such as mean, standard deviation, entropy, energy, and ignore spatial relationships among them. On the other hand, second-order statistical methods capture numerical features of a texture using spatial relations of similar gray values. Gray level co-occurrence matrices (GLCM) [7], autocorrelation function [8], and local binary pattern operator [9] are the most popular second-order statistics for texture description. Higher order statistical features maybe more accurate but they are not applicable in real-time applications due to computational complexity [10].

This paper is organized as follows. Section 2 reviews the background literature of original LBP and related works. The preprocessing steps of our method to achieve a scale- and rotation-invariant LBP descriptor are presented in Section 3. Section 4 presents the proposed new weighting LBP scheme. Experimental results are given in Section 5. Finally, conclusions are given in Section 6.

2. Original LBP and related works

Since its introduction in 1996 for texture classification [11], Local Binary Patterns (LBP) have been utilized in various

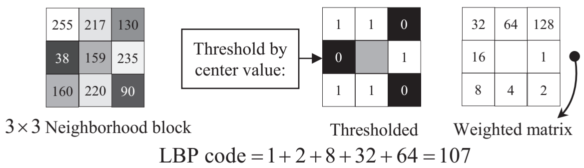

Fig. 1. The basic LBP operator.

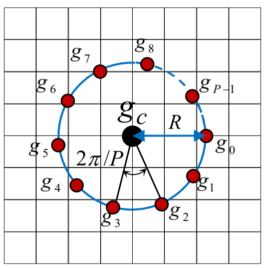

Fig. 2. Circularly symmetric neighborhoods with radius R and P neighborhood pixels.

image analyses applications such as dynamic texture recognition [12], 3D face recognition [13], text detection [14], music genre classification [15], image forgery [16], image region descriptors [17,18] and so on. The great interest to LBP is mainly due to its low computational complexity and high robustness to local variations [9]. In the basic form of LBP, gray level value of each pixel is determined by its neighboring pixels located in a 3×3 block. According to Fig. 1, first the central pixel is compared with its adjacent pixels. Then, this binary pattern is multiplied by a weighted matrix with powers of two. Finally, the central pixel value is obtained by summation of these weighted elements. Since 3×3 neighborhood block may not accurately represent large scale structures, the basic LBP was extended to include all circular neighborhoods with any number of pixels as shown in Fig. 2.

Let $I(x,y)$ be a gray level image and g_c indicates the gray level of an arbitrary pixel positioned at (x_c,y_c), i.e. $g_c=I(x_c,y_c)$. Gray values of P equally spaced circular neighborhood pixels on a circle of radius $R(R>0)$, around g_c are shown by g_p, $p=1,1,\ldots,P-1$. The extended LBP form shown by $LBP_{P,R}(x_c,y_c)$ is obtained as follows:

$$g_p=I(x_p,y_p),\quad p=0,\ldots,P-1$$

$$x_p=x_c+R\cos(2\pi p/P)$$

$$y_p=y_c-R\sin(2\pi p/P)$$

$$LBP_{P,R}(x_c,y_c)=\sum_{p=0}^{P-1}s(g_p-g_c)2^p$$

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

According to Eq. (1), when a certain block in an image is rotated, the neighborhoods around the central pixel are changed accordingly. To achieve rotation invariance, the original LBP code is circularly rotated to obtain minimum value [9], (Eq. (2)). The algorithm is shown by a simple example in Fig. 3.

$$LBP^{ri}_{P,R}=\min\{ROR(LBP_{P,R},i)\,|\,i=0,1,\ldots,P-1\}\tag{2}$$

where the superscript "ri" stands for "rotation invariant". The function $ROR(x,i)$ circularly shifts the P-bit binary number x, i times to the right ($|i|<P$).

According to statistical analysis, in Outex dataset [19], nearly 90% of all patterns in $LBP_{8,1}$ and 70% in $LBP_{16,2}$ contain at most two bitwise transitions from 0 to 1 or vice versa when binary string is considered circularly [9]. It was demonstrated that these uniform patterns represent fundamental properties of a texture [20]. The rotation invariant uniform code ($LBP^{riu2}_{P,R}$) is calculated by rotating the uniform code to its minimum value.

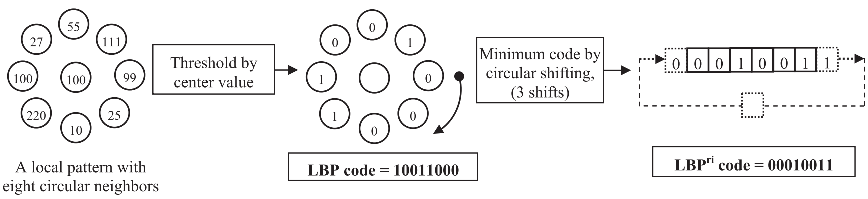

Fig. 3. An example of original LBP and rotation invariant LBP.