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Local multiple patterns based multiresolution gray-scale and rotation invariant texture classification

Changren Zhu *, Runsheng Wang

ATR National Lab., National University of Defense Technology, China

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A B S T R A C T

The local binary pattern (LBP) is a robust but computationally simple approach in texture analysis. However, LBP does not have enough information to discriminate among multiple patterns due to its binary patterns only comprising of 0s and 1s. Thus, a multi-resolution gray-scale and rotation invariant texture classification based on local multiple patterns (LMP) is proposed in the paper. The LMP extends binary patterns to multiple patterns, which can preserve more structural information, and be more suitable for image analysis, including the analysis of flat image areas, in which case LBP code is often a random value and thus unsuitable. In addition, several extensions to the LMP, including multi-resolution analysis with the "uniform" LMP with rotation invariance, are presented. The "uniform" LMP can be regarded as a gray-scale and rotation invariant description in various applications and its discrete occurrence histogram over a region of image is proved to be a powerful invariant texture feature. Experimental results of multi-resolution texture classification with support vector machine show that the proposed method obtains overall better performance than other common methods in several aspects of space-resolution and gray-scale variation, rotation, and noise.

1. Introduction

Analysis of two-dimensional textures is a fundamental research topic in the area of computer vision and has many potential applications, for example, in industrial surface inspection, remote sensing, and biomedical image analysis. However, it is difficult to describe texture accurately. One major problem is that textures in real world are often not uniform due to variations in orientation, scale, or other visual appearance. These factors produce great within-class variability. There are many publications [1–58] discussing the texture analysis and classification, but there exist only a limited number of examples of successful exploitation of texture. In addition, most proposed texture measures has high degree of computational complexity, as Randen and Husoy [42] concluded in their extensive comparative study involving dozens of different spatial filtering methods: "A very useful direction for future research is therefore the development of powerful texture measures that can be extracted and classified with a low-computational complexity."

The local binary pattern (LBP) operator, first introduced by Ojala et al. [36], is a robust but theoretically and computationally simple approach. It brings together the separate statistical and structural approaches to texture analysis, thereby opening a door for the analysis of both stochastic microtextures and deterministic macrotextures simultaneously. Additionally, it has shown excellent performance in many comparative studies, in terms of both speed and discrimination performance.

The original LBP operator [36] labels each 3 × 3-neighborhood pixel in each pixel of an image with a binary number by comparing gray values between the pixel and its each neighborhood pixel. The neighborhood pixel labels form the LBP code

* Corresponding author. Tel.: +86 731 4575724; fax: +86 731 4575791.
E-mail addresses: changrenzhu@yahoo.com.cn (C. Zhu), rswang@nudt.edu.cn (R. Wang).

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of the pixel. The LBP code characterizes local image texture patterns around central pixel, describing its structural information. The histogram of the codes can be used as a texture descriptor, describing its statistical information. Later the original LBP operator [36] has been extended in several ways, such as neighborhoods with different sizes [35], multi-resolution [27], uniform patterns [35], etc. The extended LBP operator can be used for rotation-invariant texture classification, and has a wide application, such as texture analysis and classification [21–42], face detection and recognition [1,2,6,10,12,16,19,20,22,45,56,36], image retrieval [43], etc.

However, the binary patterns comprising of 0s and 1s, adopted by the LBP, do not have enough information to discriminate between multiple patterns in actual images. Especially, the LBP is unsuitable for the analysis of flat image areas, where all pixels in a small neighbor have nearly equal gray values. The LBP code bit in flat image areas might be a random value of 0 or 1. The case is especially true when there is a little noise, as similarly described about the drawback of LBP in [3,14]. It results in serious unreliability of the extracted feature. This weakness cannot be overcome by the original LBP-based methods.

Later, some improvements of LBP were developed thereafter. On the one hand, a special processing was done on the zone around the center pixel value. For example, the reference value was shifted by adding a given threshold to make LBP less sensitive to noise [15] (denoted as LBP_HP). On the other hand, an extension of LBP called Local Ternary Patterns (LTP_TT), which bears some similarity to the texture spectrum (TS) technique [13], was proposed by Tan and Triggs [44] and had already been used for facial expression recognition by Gritti et al. [12]. In LTP_TT, neighboring pixel values in a zone of width $\pm t$ around the center pixel value i_c were quantized to zeros, values above this quantized to +1 and values below it to -1. Thus, LTP_TT uses a ternary code instead of a binary code. Then a coding scheme was adopted to splits each ternary pattern into its positive and negative parts, subsequently treating these as two separate channels of LBP descriptors. LTP_TT was less sensitive to noise in near-flat regions.

In this paper, focusing on rotation and gray-scale invariant texture classification, a new generalized feature description called "local multiple patterns" (LMP) is proposed. At first, our approach is to generalize LBP, TS [13] and LTP_TT to LMP. The basic idea of LMP is to extend the LBP's binary patterns to multiple patterns. With multiple patterns, LMP can preserve more information to discriminate between different patterns. Moreover, with the definition of a special zone around the center pixel value, LMP aims to be more robust for image analysis, including the analysis in flat image areas, in which case the original LBP often fails.

Furthermore, our approach is to select the certain LMP, called "uniform" LMP, which are fundamental rotation-invariant properties of local image texture and whose occurrence histogram is proven to be a very powerful texture feature. Multiresolution analysis is carried out by combining several neighbors with different sizes or shapes.

In addition, our proposed method is robust in terms of gray-scale variation because the global illumination change results in only little variation of the local relative gray-scale. The performance of the proposed approach is demonstrated with some experiments. The proposed texture operator is proved to be an excellent gray-scale and rotation invariant texture descriptor.

The paper is organized as follows. Section 2 gives a brief analysis of the LBP operator and its extensions, which are the basis of the LMP. Section 3 presents the definition and the derivation of the LMP. Section 4 gives several extensions of the LMP. Section 5 describes the multiresolution gray-scale and rotation invariant texture classification method based on the LMP. Section 6 shows several experiments. Finally discussion and conclusion are made in Section 7.

2. Analysis of local binary patterns (LBP)

2.1. Fundaments of LBP

The derivation of the LBP presented by Ojala et al. [35] is described briefly as follows. The texture T is defined as the joint distribution of the gray levels of $P+1(P>0)$ image pixels:

$$T = t(g_c, g_0, \ldots, g_{P-1}), \tag{1}$$

where g_c is the gray value of the center pixel in a local neighborhood. $g_p(p = 0,\ldots,P-1)$ corresponds to the gray values of P equally spaced pixels in a circle of radius $R(R > 0)$. Fig. 1 illustrates three circularly symmetric neighbor sets for different values of P and R [24].

To achieve invariance with respect to any monotonic transformation of the gray scale, the signs of the differences are only considered as:

$$T \approx t(s(g_0 - g_c), \ldots, s(g_{P-1} - g_c)), \tag{2}$$

$$\text{where } s(x) = \begin{cases} 1 & \text{if } x >= 0 \\ 0 & \text{if } x < 0. \end{cases} \tag{3}$$

Then, a weight 2^p is assigned to each sign $s(g_p - g_c)$ to transform the differences in a neighborhood into a unique LBP code. The code characterizes the local image texture:

$$LBP_{P,R} = \sum_{p=0}^{P-1} s(g_p - g_c)2^p. \tag{4}$$