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Adjacent evaluation of local binary pattern for texture classification ☆

Kechen Song [a,*], Yunhui Yan [a], Yongjie Zhao [a], Changsheng Liu [b]

[a] School of Mechanical Engineering & Automation, Northeastern University, Shenyang, China
[b] Key Laboratory for Anisotropy and Texture of Materials (Ministry of Education), Northeastern University, Shenyang, China

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ABSTRACT

This paper presents a novel, simple, yet robust texture descriptor against noise named the adjacent evaluation local binary patterns (AELBP) for texture classification. In the proposed approach, an adjacent evaluation window is constructed to modify the threshold scheme of LBP. The neighbors of the neighborhood center g_c are set as the evaluation center a_p. Surrounding the evaluation center, we set up an evaluation window and calculate the value of a_p, and then extract the local binary codes by comparing the value of a_p with the value of the neighborhood center g_c. Moreover, this adjacent evaluation method is generalized and can be integrated with the existing LBP variants such as completed local binary pattern (CLBP) and local ternary pattern (LTP) to derive new image features against noise for texture classification. The proposed approaches are compared with the state-of-the-art approaches on Outex and CUReT databases, and evaluated on three challenging databases (i.e. UIUC, UMD and ALOT databases) for texture classification. Experimental results demonstrate that the proposed approaches present a solid power of texture classification under illumination and rotation variations, significant viewpoint changes, and significant large-scale challenging conditions. Furthermore, the proposed approaches are more robust against noise and consistently outperform all the basic approaches in comparison.

1. Introduction

Texture is an inherent characteristic in visual scenes and contains important information about the structural arrangement of surfaces, e.g., the surfaces of wood, fabric, crops in a field, and many more. Texture analysis is a fundamental issue and also an active research topic over several decades in image processing, pattern recognition, computer vision, and other related fields. Texture classification, as the most important part in texture analysis, is a discriminative technique aiming at assigning an unseen texture sample into one of predefined classes.

A wide variety of approaches for texture classification have been proposed since the initial research in the 1960s [1]. Tuceryan and Jain [2] divided these approaches into five major categories: statistical, geometrical, structural, model-based, and signal processing approaches. Actually, the statistical, model-based, and signal processing approaches are the most commonly used. The statistical approaches use the statistical features to describe the textures [3,4]. In the model-based approaches, the texture image is modeled as a probability model or as a linear combination of a set of basis functions [5], e.g., auto-regressive model [6] and Orthogonal polynomials model [7]. The signal processing approaches are generally recognized as filtering approaches [8], in which the texture image is analyzed by filters, including Fourier filters [9], Gabor filters [10], Wavelet filters [11], Morphological filters [12], and spatial filters [13,14].

More recently, Local Binary Pattern (LBP) proposed by Ojala et al. [15] has been known as one of the most successful statistical approaches for texture classification. LBP is a simple yet efficient descriptor to describe local image patterns, and has been adapted to many applications, such as dynamic texture recognition [16], human actions recognition [17], and more others [18]. It is considered as an active research tool for texture classification due to its attractive properties including gray-scale and rotation invariant. However, the conventional LBP suffers from several limitations, e.g., the large number of patterns and the sensitivity to noise. In recent years, lots of improved approaches have been proposed to address these limitations.

In order to extract more discriminative patterns, several approaches took full advantage of non-uniform patterns. For instance, the work of Zhou et al. [19] analyzed the structure and occurrence probability of non-uniform patterns, and classified all the non-uniform patterns into different subsets. Liao et al. [20] proposed dominant LBP (DLBP) which made use of the most

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* Corresponding author.
E-mail address: unkechen@gmail.com (K. Song).

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frequently occurred patterns of LBP to improve the classification accuracy. Very recently, Guo et al. [21] applied a three-layered model to learn the optimal pattern subset using the Fisher's separation criteria.

To construct the contrast information and complementary features, a wide variety of approaches have been proposed. For instance, Heikkilä et al. [22] exploited center-symmetric LBP (CS-LBP) which combined the strengths of the well-known SIFT descriptor and the LBP texture operator. Guo et al. [23] developed the completed LBP (CLBP) which included the information contained in the magnitudes of local differences as complementary to the signs of LBP. Moreover, Zhao et al. [24] totally abandoned the local binary structural information in completed local binary count (CLBC) yet achieved comparable classification accuracy with CLBP. Tan and Triggs [25] extended the original LBP to 3-valued codes, i.e., local ternary pattern (LTP). Guo et al. [26] treated the variance of each point as weight of code value, i.e., LBP variance (LBPV). Recently, Liu et al. [27] presented an extended LBP, in which two different and complementary types of features were extracted from local patches and four descriptors were developed. Besides, there are other related variants such as joint distributions of local patterns [28], local energy pattern (LEP) [29], and histograms of equivalent patterns (HEP) [30].

In order to make the LBP more robust against the interference of noise, Khellah [31] extracted a global texture feature named dominant neighborhood structure (DNS) and combined it with LBP. Although the DNS descriptor can resist noise, the scheme of LBP operator did not change and was still sensitive to noise. Fathi et al. [32] proposed the noise tolerant LBP (NTLBP) which made use of the circular majority voting filtering to reduce the noise effect. Recently, Maani et al. [33] exploited the local frequency descriptors (LFD) which took advantage of the local frequencies to create noise robust features. Both of the NTLBP and the LFD utilized filters to provide noise robust features, but the threshold scheme of LBP was not modified. Hence, the limitation of the threshold scheme is not radically resolved, i.e., the threshold scheme of LBP is still sensitive to noise.

The fundamental question for this study is: how to modify the threshold scheme of LBP so that the LBP and its variants can be more robust against noise. Motivated by the estimated neighborhood structure in DNS [31], a novel, simple, yet robust texture descriptor against noise named the adjacent evaluation local binary patterns (AELBP) is proposed for texture classification. In the proposed approach, the adjacent evaluation window which is around the neighbor is constructed to modify the threshold scheme of LBP. In addition, this adjacent evaluation method is generalized and can be integrated with the existing LBP variants such as completed local binary pattern (CLBP), completed local binary count (CLBC) and local ternary pattern (LTP) to derive new image features against noise for texture classification. Moreover, experimental results demonstrate that the adjacent evaluation window plays an important role in solving the issue of sensitive to noise in LBP.

The rest of this paper is organized as follows: Section 2 presents the proposed AELBP, AECLBP and AELTP in detail. Then Section 3 elaborates the experiments and discusses the experimental results. Finally, Section 4 concludes the paper.

2. Adjacent evaluation

In this section, an approach named the adjacent evaluation local binary pattern (AELBP) for texture classification is given in Section 2.1. Since the adjacent evaluation method is generalized and can be integrated with the existing LBP variants, the adjacent evaluation completed LBP (AECLBP) and the adjacent evaluation LTP (AELTP) are derived for texture classification in Sections 2.2 and 2.3 respectively. Finally, the multi-scale analysis and classification of these approaches are presented in Section 2.4.

2.1. Adjacent evaluation LBP (AELBP)

In the conventional LBP operator, local binary codes are extracted by comparing the values of neighborhood pixels with the value of the central pixel and then are encoded to form the local binary patterns. However, this conventional encoding strategy is especially vulnerable to noise, i.e., the values of the neighbors can be easily changed by random noise, making the local binary patterns unstable. Concerning this issue, we try to construct an adjacent evaluation window which is around the neighbor to reduce the interference of noise. Moreover, inspired by the encoded strategy of LBP, we propose an approach named the adjacent evaluation local binary patterns (AELBP), which can be considered as an extension of LBP. The proposed AELBP is defined as follows:

$$\mathrm{AELBP}_{P,R} = \sum_{p=0}^{P-1} s(a_p - g_c)2^p, \quad s(x) = \begin{cases} 1 & x \geqslant 0 \\ 0 & x < 0 \end{cases} \tag{1}$$

where P points spaced equidistantly around a circle of radius R, g_c is the grayscale value at central point, and a_p is set as the average value of the pth evaluation window excluding the value of evaluation center.

Obviously, the main difference between the LBP and the AELBP is that AELBP replaces the g_p with a_p. The entire operation procedure of the AELBP mainly includes the following two steps:

(1) **Calculating the value of a_p.** Set the neighbor which is around the neighborhood center g_c as the evaluation center a_p. Surrounding the evaluation center, we set up an evaluation window of size $W \times W$ (W can only be odd numbers). Then, excluding the pixel value of the evaluation center, the value of a_p is obtained by calculating the average of the remaining values in the p^{th} evaluation window. What needs to be noted is that when the value of W is set as 1, AELBP is equivalent to the conventional LBP.

(2) **Forming the local binary patterns**. Local binary codes are extracted by comparing the value of a_p with the value of the neighborhood center g_c. Then, the local binary codes are encoded to form the patterns.

In order to better explain the entire operation procedure of AELBP, Fig. 1 illustrates a specific example of $\mathrm{AELBP}_{8,1}$ (W is set as 3). As is shown in Fig. 1, the value of evaluation center a_p in the 4th evaluation window (i.e. the dashed square) is 152. According to the calculation method mentioned above, the rest of the values of a_p at other evaluation windows can be obtained (i.e. the bottom left square of solid lines). The value of g_c (i.e. 118) is compared with the other eight a_p values through the function $s(x)$. Then, the local binary codes are encoded to form the patterns (i.e. "11111111").

2.1.1. Application example analysis

To illustrate the effectiveness of AELBP, Fig. 2 gives a comparison in terms of the robustness to additive Gaussian noise (SNR = 20 dB) between the proposed AELBP (W is set as 3) and the conventional LBP on the Outex texture image (canvas011). The original texture image is shown in Fig. 2(a) and the corresponding image with additive Gaussian noise is shown in Fig. 2(b). Fig. 2(c) and Fig. 2(d) are 5×5 pixel region, extracted from the same location (i.e. bottom left) of the corresponding image, respectively. The patterns of LBP for corresponding pixel region,