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Local directional ternary pattern: A New texture descriptor for texture classification☆

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ABSTRACT

In this paper, the three level descriptions from LTP and the directional features from LDP are combined to form a new local feature descriptor, referred to as local directional ternary pattern (LDTP) for texture classification. LDTP is a framework, which consists in encoding both contrast information and directional pattern features in a compact way based on local derivative variations. To achieve robustness, the proposed operator first computes for each pixel within its 3 × 3 overlapping grayscale image patch, on the one hand, eight directional edge responses using the eight Frei–Chen masks, and on the other hand, central edge response through the 2nd derivative of Gaussian filter to capture more detailed information. This allows producing a more discriminative encoding than several state-of-the art methods based only on intensity information. Then, spatial relationships among the neighboring pixels through the edge responses are exploited independently with the help of both LDP's and LTP's concepts to enhance the discrimination capability. Indeed, the implicit utilization of both concepts of LTP and LDP encodes more information in comparison to the existing directional and derivative methods in less space, and simultaneously allows discriminating more textures. Finally, the resultant LDTP pattern is divided into two distinct parts: local directional ternary pattern upper ($LDTP_U$) and local directional ternary pattern lower ($LDTP_L$), and the final feature descriptor vector is obtained by linear concatenation of both $LDTP_U$ and $LDTP_L$ histograms. The experiments carried out on nine publicly available texture datasets demonstrated that the proposed LDTP descriptor achieves classification performance, which is competitive or better than several recent and old state-of-the-art LBP variants. Statistical significance of the achieved accuracy improvement by the proposed descriptor has been also demonstrated through the Wilcoxon signed rank test applied on all the tested datasets.

1. Introduction

Texture analysis has been widely used in computer vision and pattern recognition applications due to its potential in extracting prominent features. Texture feature extraction as one of the major problems in texture analysis, has been a long-standing research topic (Mirmehdi, 2008; Nanni et al., 2012) due to its significance in understanding how the texture recognition process works in humans as well as the important role it plays in wide variety of computer vision and image analysis based applications. Applications like face detection and recognition (Nanni et al., 2017), object and scene recognition (Torralba et al., 2008), sky extraction from fisheye images (Merabet et al., 2017a; 2017b), background subtraction (Kim and Kim, 2012), pedestrian detection (Zheng et al., 2017), food inspection (Zheng et al., 2006), computer assisted diagnosis (Remeseiro et al., 2016), surveillance systems (Xue et al., 2013), motion and activity analysis (Elharrouss et al., 2015) and many more, are just some examples where texture analysis can be successfully exploited.

Over the last decades, many texture feature extraction methods have been proposed to characterize textured images. One can cite traditional approaches like the use of fractal analysis (Xu et al., 2006; 2009; 2010), co-occurrence matrix-based approaches (Davis, 1981) and filter-based methods such as Gabor (Manjunath and Ma, 1996), wavelet (Porter and Canagarajah, 1997) and Gaussian Markov random fields (Cohen et al., 1991). The method proposed in Duvernoy (1984) consists in extracting texture feature in spectrum domain by using Fourier descriptors. Goyal et al. (1995) proposed texel property histogram based method. The authors in Chen and Kundu (1992) proposed a texture recognition method based on hidden Markov model (HMM) and multichannel sub-bands decomposition. Alata et al. (1998) used 2-D

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spectrum domain to calculate a set of texture descriptors. Texton dictionary-based (Varma and Zisserman, 2003; 2005; 2009) methods have additionally been utilized in texture analysis field.

In recent years, active researches in texture feature extraction focus on pattern based features, due to their effectiveness and the ease of their extraction from textured images. LBP based methods, due to their outstanding performance, have emerged as one of the most prominent texture descriptors. Ojala et al. (1996a) first proposed local binary patterns (LBP) operator which has been known as one of the most successful statistical approaches for texture representation and classification. LBP descriptor transforms an image into an array of codes describing its small-scale appearance (e.g. flat areas, spots, etc.). The computation of LBP consists of two main steps: 1) extracting binary patterns (i.e. texels or textons) of spatially local elementary microstructures in the texture image and 2) analyzing the histogram distribution of these patterns. LBP descriptor, which offers invariance against monotonic gray level changes, has been thereafter successfully applied in many research areas such as medical image analysis (Nanni et al., 2010), face recognition (Li et al., 2006; Zhang et al., 2004; 2005), facial expression recognition (Shan et al., 2005), image retrieval (Murala et al., 2012), object detection (Satpathy et al., 2014), remote sensing (Musci et al., 2013), texture classification (Ojala et al., 2002), motion detection (Lin et al., 2015), biomedical image analysis (Pietikäinen, 2005), finger vein recognition (Xie et al., 2012) and background subtraction (St-Charles and Bilodeau, 2014).

Following the success of LBP in this large variety of applications, a vast number of LBP variants have been proposed to improve the discrimination capability, robustness and applicability of LBP. Indeed, LBP's success has led to much research toward extensions tackling various issues and needs. Representative methods include center-symmetric LBP (CS-LBP) (Heikkilä et al., 2006), local ternary pattern (LTP) (Tan and Triggs, 2010), completed LBP (CLBP) (Guo et al., 2010a), LBP variance (LBPV) method (Guo et al., 2010c), local directional patterns (LDP) (Jabid et al., 2010a), enhanced LDP (EnLDP) (Zhong and Zhang, 2013a), local directional number (LDN) patterns (Rivera et al., 2013), Extended local binary patterns (Abdullah et al., 2014), local binary patterns by neighborhoods (nLBP_d) (Kaya et al., 2015), etc.

Center-symmetric LBP (CS-LBP) proposed by Heikkilä et al. (2006) combines the strengths of the well-known SIFT descriptor and the LBP texture operator. Local ternary pattern (LTP) introduced by Tan and Triggs (2010) for face recognition, which extends original LBP to 3-valued codes using a threshold, is more insensitive to noise than LBP. However, LTP is not strictly invariant to gray-scale changes, and the selection of suitable threshold values is not easy. The completed LBP (CLBP) operator, developed by Guo et al. (2010a) for texture classification, uses the magnitude of local differences as complementary information to the signs of LBP. The LBPV method introduced in Guo et al. (2010c) consists in incorporating local contrast and global orientation information into LBP histogram. BGC1, BGC2 and BGC3 operators proposed by Fernández et al. (2011) are based on pairwise comparison of adjacent pixels belonging to one or more closed paths traced along the periphery of 3 × 3 neighborhood. The four LBP-like descriptors (two local intensity-based ones CI-LBP and NI-LBP and two local difference-based ones RD-LBP and AD-LBP), along with multiscale joint histogram features NI/CI/LBP, NI/RD/LBP and NI/RD/CI/LBP, proposed by Abdullah et al. (2014), extract complementary texture information of local spatial patterns. In local binary patterns by neighborhoods (nLBP_d) operator, proposed by Kaya et al. (2015), the comparison between the peripheral pixels is done with sequential neighbors and/or inside neighbors defined by a distance parameter d. LDP-like operators such as LDP (Jabid et al., 2010a), EnLDP (Zhong and Zhang, 2013a) and LDN (Rivera et al., 2013) produce eight directional edge images using Kirsch compass masks and encode the directional information to obtain noise and illumination-invariant representation.

As will be pointed out later (see Section 3), most of the above state-of-the-art methods come with limitations and weaknesses. In order to avoid these limitations and keep the simplicity and effectiveness of the traditional LBP, we propose a conceptually and computationally simple yet efficient texture descriptor referred to as local directional ternary pattern (LDTP) for texture classification. LDTP operator extracts higher-order local information by encoding various distinctive spatial microstructures within a given local region. The main advantage of the proposed descriptor over the existing ones is that it combines both the concepts of LTP-like and LDP-like operators in the same compact encoding scheme, which provides more detailed and discriminated information. Specifically, the major contributions of this work are summarized as follows:

- A new LBP-and-LDP-like operator is proposed: local directional ternary pattern (LDTP) for texture classification. As we will show later, this new encoding scheme is more useful to understand texture images than basic LTP-like and LDP-like operators, since it conveys valuable information about the nature of textures by capturing local structures using both LTP's and LDP's concepts simultaneously.
- An automatic method for optimal user-specified parameters selection through statistical hypothesis testing based ranking technique (Wilcoxon signed rank test), is proposed.
- This paper provides fair, systematic and comprehensive comparison between the proposed descriptor and large number of old and recent state-of-the-art methods, which has been rarely performed in the texture classification field.
- Unlike most researches reported in the literature, where comparisons between evaluated descriptors are carried out only on each tested dataset, performance stability of the evaluated methods over several texture datasets, is also investigated in this paper.
- Statistical significance of the achieved accuracy improvement has been also demonstrated using Wilcoxon signed rank test.
- Extensive experiments were conducted on nine challenging representative texture datasets. High performance has been achieved by the proposed model when compared against the evaluated state-of-the-art methods.

The remainder of this paper is organized as follows. Section 2 briefly presents some existing variants of local patterns. Section 3 presents the proposed LDTP descriptor. Comprehensive experimental results and comparative evaluation are given in Section 4. Section 5 concludes the paper and proposes some future research directions.

2. Variants of local patterns

In this section, we review some LBP variants such as, local binary pattern (LBP), local ternary pattern (LTP) and local directional pattern (LDP).

2.1. Local binary pattern (LBP)

Ojala et al. (1996a) introduced the concept of local binary pattern (LBP) for texture classification. For each pixel in a textured image, a binary pattern is obtained by comparing its value with those of its neighbors in each 3 × 3 square neighborhood in the image. Given a central pixel in a 3 × 3 grayscale image patch, the corresponding LBP value is calculated based on Eqs. (1) and (2).

$$LBP = \sum_{p=0}^{7} 2^p \xi(\mathscr{I}_p - \mathscr{I}_c) \tag{1}$$

$$\xi(x) = \begin{cases} 1 & \text{if } x > =0, \\ 0 & \text{else} \end{cases} \tag{2}$$

where $\mathscr{I}_p$ is the gray value of the neighbors of the central pixel, which has gray value $\mathscr{I}_c$. Fig. 1 shows an example of LBP calculation in a 3 × 3 square neighborhood. LBP generates 2^8 possible different patterns.