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Local Concave-and-Convex Micro-Structure Patterns for texture classification

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ABSTRACT

Motivated by researching new image texture modeling that improves state-of-the-art LBP variants and non-LBP descriptors, this paper proposes a novel approach for constructing local image descriptors, which are suitable for histogram based image representation. Instead of heuristic code constructions, the proposed approach is based on local concave-and-convex characteristics, which have high ability to extract discriminative and stable texture representation. Different from the majority of descriptors that only encode relationships between the pixels in doublets around central pixel (within 3×3 neighborhood), the proposed approach encodes relationships between the pixels in triplets by including the central pixel in the modeling. We build two distinct descriptors by dividing local features into two distinct groups, i.e., local concave and convex microstructure patterns (LCvMSP and LCxMSP), according to relationships between the pixels inside the triplets, formed along closed path around the central pixel of a 3×3-grayscale image patch. To make the descriptors more insensitive to noise and invariant to monotonic gray scale transformation, two supplementary triplets are added in the modeling. These triplets are formed using the central pixel and four virtual pixels set to the median of the grey-scale values of the 3×3 neighbourhood and the whole image and the average local and global gray levels respectively. The histograms obtained from the single scale descriptors LCvMSP and LCxMSP are concatenated together to build multiscale histogram feature vector referred to as local concave-and-convex micro-structure pattern (LCCMSP), that is expected to better represent salient local texture structure. We evaluated the effectiveness of the proposed methods on thirteen challenging representative widely-used texture datasets, and found that the proposed LCvMSP, LCxMSP and LCCMSP operators achieve performances that are competitive or better than a large number of recent most promising state-of- the-art LBP variants and non-LBP descriptors. Statistical comparison based on Wilcoxon signed rank test demonstrated that the proposed methods are the top three over all the tested datasets.

1. Introduction

Objects like human skin, fabric, natural scenes, crops in a field, surface of materials and many more are characterized by their own distinct texture. The analysis of this important characteristic, which contains useful information about the structural arrangement of surfaces has been the subject of several applications including material classification, scene understanding, face detection and recognition, pedestrian detection, background subtraction, etc. It is then an area of active research topic in image processing, pattern recognition, computer vision, and other related fields.

A wide variety of approaches for texture analysis have been proposed in the literature, including random features [10], human perception-based features [12], methods based on the ranklet transform [11], filter-based methods such as Gaussian Markov random fields [7], wavelet [9] and Gabor [1], use of fractal analysis [16–18], and co-occurrence matrix-based approaches [2]. Duvernoy [4] proposed to extract texture feature in spectrum domain by using Fourier descriptors. The method proposed in [5] is based on texel property histogram. Chen and Kundu [8] proposed a texture recognition method based on hidden Markov model (HMM) and multichannel sub-bands decomposition. Alata et al. [6] used 2-D spectrum domain to calculate a set of texture descriptors. Texton dictionary-based [13–15] and LBP-based [3] methods have additionally been utilized in texture analysis field.

Among the above approaches, LBP-based methods have emerged as one of the most prominent texture descriptors, be-

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cause of their outstanding performance. Ojala et al. [3] first introduced the LBP method in 2002. Although originally proposed for texture analysis, the LBP method has been successfully applied in diverse range of problems including face description and recognition, dynamic texture recognition, medical image analysis, outdoor scene analysis, motion detection, image retrieval, biomedical image analysis, object detection, remote sensing, fingerprint matching and background subtraction. Since Ojala's work, a vast number of LBP variants have been proposed and continue to be developed. Heikkilä et al. [37] proposed center-symmetric LBP (CS-LBP) which combines the strengths of the well-known SIFT descriptor and the LBP texture operator. Guo et al. [68] developed a completed modeling of LBP to produce CLBP (Completed Local Binary Pattern) which combines the magnitudes of local differences as well as their signs. The method consists in converting the gray level of the central pixel into a binary code, namely CLBP-Center (CLBP_C), using a global threshold. The image local differences yield two complementary components: sign and magnitude. Two operators, namely CLBP-Sign (CLBP_S which is therefore the same as the original LBP) and CLBP-Magnitude (CLBP_M), are then defined to code the sign and magnitude of the image local differences, respectively. Guo et al. [67] proposed LBPV method which incorporates local contrast and global orientation information into LBP histogram. Tan et al. [46] proposed a local ternary pattern (LTP) for face recognition. LTP, which extends original LBP to 3-valued codes using a threshold, is introduced to reduce noise sensitivity of the original LBP. Keramidas et al. [29] proposed fuzzy local binary pattern (FLBP) which extends the LBP operator by incorporating fuzzy logic in the representation of local patterns of texture. FLBP assumes that a local neighborhood can be partially characterized by more than one binary pattern as a result of noise-originated uncertainty in the pixel values. Fernández et al. [30] proposed a family of descriptors referred to as Binary gradient contours (BGC1, BGC2 and BGC3) based on pairwise comparison of adjacent pixels belonging to one or more closed paths traced along the periphery of 3×3 neighborhood. Liu et al. [74] proposed four LBP-like descriptors to extract complementary texture information of local spatial patterns, two local intensity-based CI-LBP and NI-LBP, and two local difference-based descriptors RD-LBP and AD-LBP, along with multiscale joint histogram features NI/CI/LBP, NI/RD/LBP and NI/RD/CI/LBP. Recently, Kaya et al. [20] proposed local binary patterns by neighborhoods ($nLBP_d$) where the comparison between the peripheral pixels is done with sequential neighbors and/or inside neighbors defined by a distance parameter d. Ouslimani et al. [54] proposed the local directional rank coding (LDRC) method for multi-scale texture classification. LDRC operator collects directional information representing the rank order of the central pixel gray level calculated in four principal orientations in 3×3 neighborhood pixel. Zhao et al. [53] proposed local quantization code histogram (LQCH) to validate the performance of different local quantization levels. The pixels located in different quantization levels are separately counted and the average local gray value difference is used to set a series of quantization thresholds.

Although LBP has gained great success in pattern recognition and most extensions of LBP have improved the performance of LBP, they still, as will be shown later, suffer from an inborn defect of LBP.

In this paper, keeping the simplicity and effectiveness of the basic LBP and addressing its weakness, we propose conceptually simple, high-quality and yet robust frameworks of LBP, referred to as LCvMSP (Local Concave Micro-Structures Pattern), LCxMSP (Local Convex Micro-Structures Pattern) and LCCSMP (Local Concave-and-Convex Micro-Structures Pattern). The proposed methods have the following outstanding advantages: As it will be shown further, they allow considerably enhancing both the discriminative power of LBPs and their robustness to small variations, due to image noise, and have low computational complexity. At the feature extraction stage, there is no pre-learning process and no additional parameters to be learned. The main contributions of this paper are as follows:

- We introduce a formal definition of Concave and Convex Binary Thresholding Functions based on the concept of Local Concave-and-Convex Micro-Structures which provides an important gray-scale local micro-pattern.
- We propose two new LBP-like descriptors: Local Concave Micro-Structures Pattern (LCvMSP) and Local Convex Micro-Structures Pattern (LCxMSP) descriptors, which are more effective for image texture analysis /understanding than traditional LBP and a large number of old and recent LBP-like and non-LBP descriptors.
- We further extend LCvMSP and LCxMSP to incorporate multi-scale by concatenating them into a single vector feature to obtain LCCMSP descriptor which should be more robust and stable.
- An automatic statistical hypothesis testing based technique for user-specified parameters optimization for parametric methods on several texture datasets is proposed. Unlike researches reported in the literature using comparison protocol consisting in optimizing the parameter values for each dataset, we opted to define user-specified parameters of a given method that yield satisfying classification results on several datasets.
- For experimental evaluation, we restrict ourselves to the original application of LBP: texture classification. Extensive evaluation on thirteen challenging representative texture datasets is performed, showing that the proposed methods demonstrate superior performance to a large number of old and recent state-of-the-art LBP variants and non-LBP methods.

The remaining sections are structured as follows: Section 2 briefly presents some existing texture operators. Section 3 presents the proposed LCvMSP, LCxMSP LCCMSP descriptors. Section 4 summarizes LBP variants and non-LBP descriptors used for the comparison purposes. Comprehensive experimental results and comparative evaluation are given in Section 5. Section 6 concludes the paper and proposes some future research directions.

2. Revisiting the existing methods

In this section, we present a brief review of the main approaches reported in literature and from which we are inspired to define our own texture descriptors. Since, the texture operators we propose are based on local kernel functions, it is convenient to define the 3×3 square neighborhoods used in this paper. This choice is supported both by isotropy and easiness-of-implementation considerations, as well as by the fact that most applications reported in literature, like real time applications, are based on this setting. Consider a generic image $\mathbf{I}$ and let $\mathbf{x}_{m,n}^{3\times3}$ be the set of gray-scale values of a 3×3 square neighborhood centered at the pixel coordinates (m,n):

$$\mathbf{x}_{\mathbf{m},\mathbf{n}}^{3\times3} = \begin{bmatrix} \mathbf{I}_{\mathbf{m}-1,\mathbf{n}-1} & \mathbf{I}_{\mathbf{m}-1,\mathbf{n}} & \mathbf{I}_{\mathbf{m}-1,\mathbf{n}+1} \\ \mathbf{I}_{\mathbf{m},\mathbf{n}-1} & \mathbf{I}_{\mathbf{m},\mathbf{n}} & \mathbf{I}_{\mathbf{m},\mathbf{n}+1} \\ \mathbf{I}_{\mathbf{m}+1,\mathbf{n}-1} & \mathbf{I}_{\mathbf{m}+1,\mathbf{n}} & \mathbf{I}_{\mathbf{m}+1,\mathbf{n}+1} \end{bmatrix} \tag{1}$$

In a more manageable way and for the sake of simplicity, the set of gray-scale values of a 3×3 neighborhood $\mathbf{x}$ can be written as follows:

$$\mathbf{x} = \begin{bmatrix} \mathbf{I}_7 & \mathbf{I}_6 & \mathbf{I}_5 \\ \mathbf{I}_0 & \mathbf{I}_c & \mathbf{I}_4 \\ \mathbf{I}_1 & \mathbf{I}_2 & \mathbf{I}_3 \end{bmatrix} \tag{2}$$