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Mixed co-occurrence of local binary patterns and Hamming-distance-based local binary patterns

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ABSTRACT

Local binary patterns (LBP) have powerful discriminative capabilities. However, traditional methods with LBP histograms cannot capture spatial structures of LBP codes. To extract the spatial structures of an LBP code map, we compute and encode the Hamming distances between LBP codes of a center point and its neighbors on the LBP code map to generate a new code, which is called Hamming-distance-based local binary patterns (HDLBP). Then, we calculate a joint histogram of LBP and HDLBP to represent the LBP co-occurrence with HDLBP (LBPCoHDLBP). Circular bit-wise shift techniques are used to align HDLBP with LBP for rotation invariance. To achieve scale invariance, we extract the feature of LBPCoHDLBP from each scale and concatenate all features of different scales. Finally, we use the sum of absolute differences (SAD) between the intensities of the center point and its neighbors to weight LBPCoHDLBP for further improvement. Extensive experiments show that our method achieves better performance for smoke detection, texture classification and material recognition than most existing methods and is more computationally efficient.

1. Introduction

Texture analysis plays an important role in many applications [5,44], such as face recognition, image retrieval, object detection and tracking, smoke detection, and scene analysis. As the demands of these applications have rapidly increased, texture-based feature extraction methods have been widely studied. There are many texture extraction methods, such as local binary patterns (LBP) [28], co-occurrence matrices [31], Gabor filters and wavelet transformations [22]. These texture classification methods usually focus on the statistical measures of visual cues, such as the means, variances, moments and histograms. Texture classification encounters some common problems, such as variations in scale, illumination, and rotation.

LBP, which was proposed by Ojala et al. [28], is an efficient gray-scale texture operator that captures the spatial characteristics of gray-scale images. To further improve the performance, many LBP variants have been proposed in recent years. These methods have demonstrated very powerful discriminative capabilities, low computational complexities, and low sensitivities to illumination variations. LBP-based feature extraction methods have been widely studied and successfully applied in face recognition [1], texture classification [5], and smoke detection [44–46].

LBP is also a simple yet effective descriptor for texture classification in the context of smoke detection. An easy way to detect smoke from images is to directly make use of existing methods, which were proposed for specific applications, such

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as object detection, face recognition, and texture classification. However, these methods cannot be used directly to achieve satisfactory results because of large variations in smoke shape, texture and color. In previous work, dynamic and static features are often used for video smoke detection [9,10,42,43]. To improve smoke recognition accuracy, several LBP-based methods have been proposed [44–46] for smoke detection, which demonstrate excellent performance.

Spatial co-occurrences of features can be used to extract strong correlations between different features. Additionally, spatial co-occurrences of features enlarge supporting regions and provide higher-order statistical information than individual features. Previous work [40] has shown that spatial co-occurrences of features can increase classification accuracy. For example, Qi et al. [29] proposed pairwise rotation-invariant co-occurrence local binary patterns (PRICoLBP) for achieving transformation invariance, and they justified the effectiveness of the co-occurrence of features. Direct co-occurrences of features can be used to obtain higher recognition accuracy, but require many predefined offsets to cover most structures, which inevitably leads to high-dimensional joint histograms. To achieve rotation invariance, some methods need to align the encoding coordinates with the local gradient orientation of each pixel [29]. However, such complex alignment is time-consuming, despite the high accuracy.

In this paper, we encode the co-occurrence of LBP and HDLBP features to improve the accuracy of smoke detection, texture classification and material recognition. In addition, we need to achieve a balance among discriminative capabilities, feature dimensions and computational efficiency. To achieve this goal, we first propose Hamming-distance-based LBP (HDLBP) for encoding the spatial co-occurrence of LBP codes in local neighborhoods. Encoding of Hamming distances between LBP codes can reduce the dimension of the direct spatial co-occurrence of LBP codes. To further improve performance, we present the mixed co-occurrence of LBP and HDLBP (LBPCoHDLBP) for capturing complex structures that are contained in LBP and HDLBP. The main contributions of this paper are highlighted as follows:

- We encode Hamming distances between LBP codes of a center point and its neighbors to generate Hamming-distance-based LBP (HDLBP) in a similar way to LBP.
- We adopt joint histograms of LBP and HDLBP to present the mixed co-occurrence of LBP and HDLBP (LBPCoHDLBP). In addition, we use the sum of absolute differences (SAD) between the pixel intensities of the center point and its neighbors to weight LBPCoHDLBP for further improvement.
- We use the technique of circular right shift to efficiently align HDLBP with LBP. In this way, we obtain rotation invariance for LBPCoHDLBP, while avoiding complex alignments of local sampling coordinates with image gradients. Furthermore, we extend LBPCoHDLBP to the scale space of images to achieve scale invariance.

This paper is organized as follows: Section 2 briefly introduces related work on LBP and its variants. Section 3 presents local binary patterns that are based on Hamming distances. In Section 6, we propose the mixed co-occurrence of LBP and HDLBP. Section 5 presents extensive experiments for comparison. In the final section, the conclusions of this paper are presented.

2. Related work

Early LBP variants were proposed by modifying neighborhood shapes or quantization schemes. Liao and Chung [19] used an elliptic neighborhood to present elongated local binary patterns (ELBP). Jin et al. [14] proposed Improved local binary patterns (ILBP) by comparing pixel values of neighbors with the mean of these pixel values instead of the central pixel value. Local ternary patterns (LTP) [36] was designed to encode the intensity differences of neighboring pixels into ternary values instead of binary ones. Nanni et al. [25] introduced elongated ternary patterns and improved local ternary patterns. Guo et al. [12] presented completed LBP (CLBP) for texture classification, which encodes center pixel values, signs and magnitudes of local differences. Ren et al. [33] presented Noise-Resistant Local Binary Patterns by correcting uncertain bits that are polluted by noise. Zhou et al. [51] proposed a new LBP operator for classifying and combining "non-uniform" local patterns by analyzing the probabilities of structures and occurrences, which achieved higher robustness against noise than original LBPs.

Some LBP methods focus on exploring scale invariance. Qian et al. [30] extended local binary patterns to the pyramid domain to propose pyramid local binary patterns (PLBP). Li et al. [18] proposed scale- and rotation-invariant local binary patterns by dividing the uniform pattern of original LBPs into sub-uniform patterns and circularly aligning the histogram of each sub-uniform pattern according to the dominant bin with the maximum value. Yuan [44] used the scale space to propose high-order derivative local binary patterns based on circular shift sub-uniforms and scale spaces (DLBPCS).

Higher-order information also plays a key role in local patterns. Zhang et al. [48] proposed local derivative patterns (LDP) for face recognition by defining the kth order LDP as the spatial variations of the $(k-1)$th LDP. The pre-specified directions are used to estimate the variations of the $(k-1)$th-order local derivatives. Therefore, LDP results in several codes for each pixel. Guo et al. [11] encoded directional derivatives to propose local directional derivative patterns (LDDP). Yuan et al. [46] proposed high-order local ternary patterns and used locality-preserving projection to reduce dimensions for smoke detection and image classification. Vu and Caplier [39] proposed patterns of oriented edge magnitudes (POEM) for face recognition. The parameters of POEM were optimized and whitened PCA was applied to obtain a compact, robust, and discriminative descriptor [38]. Murala et al. [24] modified local tetra patterns (LTrPs) for content-based image retrieval by encoding the relationship between the referenced pixel and its neighbors. LTrPs is based on the 1st-order derivatives in the