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Globally rotation invariant multi-scale co-occurrence local binary pattern☆

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ABSTRACT

This paper proposes a globally rotation invariant multi-scale co-occurrence local binary pattern (MCLBP) feature for texture-relevant tasks. In MCLBP, we arrange all co-occurrence patterns into groups according to properties of the co-patterns, and design three encoding functions (Sum, Moment, and Fourier Pooling) to extract features from each group. The MCLBP can effectively capture the correlation information between different scales and is also globally rotation invariant (GRI). The MCLBP is substantially different from most existing LBP variants including the LBP, the CLBP, and the MSJ-LBP that achieves rotation invariance by locally rotation invariant (LRI) encoding. We fully evaluate the properties of the MCLBP and compare it with some powerful features on five challenging databases. Extensive experiments demonstrate the effectiveness of the MCLBP compared to the state-of-the-art LBP variants including the CLBP and the LBPHF. Meanwhile, the dimension and computational cost of the MCLBP is also lower than that of the CLBP_S/M/C and LBPHF_S_M.

1. Introduction

Texture cue plays an important role in many vision applications, including scene understanding, object recognition, content-based image retrieval, medical image analysis, image segmentation, and more. Due to the existence of strong rotation, illumination, and scale variations, effective description of texture information is challenging.

Local Binary Pattern (LBP) [1] shows great success on many texture-related tasks due to its strong texture discrimination and robustness to image transformations including rotation and gray-scale variations. Meanwhile, besides of texture [2–7] and material classification [8,9], the LBP and its variants have been widely applied to many applications, including face recognition [10], face detection, flower recognition [9], image retrieval, lip reading [11], and dynamic texture classification [12]. A detailed survey about the LBP and its variants can be found in [13].

To capture texture information in different image resolutions, a multi-scale strategy [2,14,8,4,5] has been introduced. Firstly, LBP histogram features are extracted separately from each scale. Then, the histograms in all scales are concatenated into a final image representation. The same multi-scale strategy are used by the LBP and most of its variants. Since the multi-scale strategy usually achieves better performance than a single scale, it is widely recognized as an indispensable means to achieve the state-of-the-art performance.

However, the classical multi-scale strategy ignores correlation among different scales. As shown at the left panel of Fig. 1, a single-scale LBP pattern depicts a kind of local image structure, but the LBP patterns in multiple scales jointly depict a stronger local structure, as shown at the right panel of Fig. 1. In fact, texture patterns in different scales around the same central point usually have strong correlation. Ignoring such correlation will lead to a huge loss of discriminative information.

To capture the correlation between different scales, we propose to jointly encode the LBPs in different scales. We summarize our key contributions as follows:

- We propose a globally rotation invariant multi-scale co-occurrence LBP (MCLBP) feature for texture-relevant tasks. In contrast to the classical multi-scale LBP (MS-LBP), our MCLBP can effectively encode the correlation that is ignored by MS-LBP. Compared to the single-scale LBP, the MCLBP can depict stronger local structures and capture richer patterns.
- We investigate the rotation invariant property of the MCLBP and introduce three simple and effective rotation invariant encoding methods. Specifically, we partition all MCLBP patterns into different groups according to the properties of the co-patterns. For each group, we can extract a rotation invariant feature using the introduced encoding methods.

We fully evaluate the properties of the MCLBP on five challenging databases. The proposed method achieves superior performance compared to the state-of-the-art LBP variants, such as CLBP_S/M/C [4],

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0262-8856/

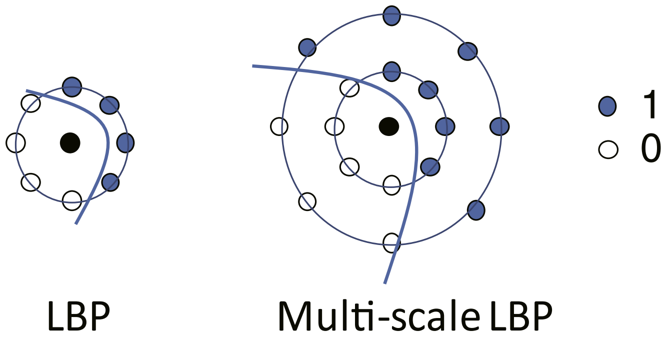

Fig. 1. An illustration of LBP and multi-scale LBP. Compared with LBP, LBPs in multiple scales jointly characterize stronger local structures.

LBPHF_S_M [6]. It also greatly improves the performance of our previous conference version (MSJ-LBP). It should be noted that, compared to some powerful LBP variants, the computational cost and feature dimension of the proposed feature is also much lower. The matlab source code of the proposed MCLBP can be downloaded from this link.[1]

2. Related works

2.1. Local Binary Pattern

LBP is an effective texture descriptor that can depict local structures of natural images, such as edge, contour and flat region. For each pixel in an image, its LBP pattern can be computed as follows:

$$LBP\left(\vec{s}\right) = \sum_{k=0}^{n-1} \phi(v_k - v_c) 2^k, \quad \phi(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0, \end{cases}$$

where $\vec{s} = [n, r]$, n is the number of neighbors and r is the radius of the neighbors. v_c is the gray value of the central pixel, and v_k is the pixel value of its k-th neighbor. $\phi(.)$ is a sign function.

In [2], Ojala et al. observed that these patterns with very few spatial transitions described the fundamental properties of the image, and they called these patterns as “uniform patterns.” The number of spatial transitions can be calculated as follows:

$$\Phi\left(LBP\left(\vec{s}\right)\right) = \sum_{k=1}^{n} |\phi(v_k - v_c) - \phi(v_{k-1} - v_c)|,$$

where v_n equals to v_0. The uniform patterns are defined as the patterns with $\Phi(LBP(s)) \leq 2$. For instance, LBP patterns “00000000” and “00001110” are the uniform patterns, while “00100100” and “01001110” are non-uniform patterns.

The uniform LBP (LBP^U) depends on the start point of the binary sequence. Here, we denote $LBP^U(s, i)$ as the uniform LBP pattern on the scale s with i as the start point of the binary sequence, where $0 \leq i \leq n - 1$.

To achieve good robustness to image rotation, Ojala et al. also introduced the concept of rotation invariant LBP (LBP^{RI}) and rotation invariant uniform LBP (LBP^{RIU}), of which LBP^{RIU} is popularly used for texture classification. The LBP^{RIU} can be defined as:

$$LBP^{RIU}\left(\vec{s}\right) = \begin{cases} \sum_{k=0}^{n-1} \phi(v_k - v_c), & \Phi\left(LBP\left(\vec{s}\right)\right) \leq 2 \\ n + 1, & otherwise, \end{cases}$$

For the number of neighbors $n = 8$, LBP has $2^8 = 256$ patterns, in which there are 58 uniform patterns as shown in Fig. 2 and 198 non-uniform patterns. Usually, all 198 non-uniform patterns are summarized into one pattern. Thus, in practice, $LBP^U(8, 1)$ has 59 patterns. According to the definintion of rotation invariant uniform LBP, the $LBP^{RIU}(8, 1)$ has 10 patterns.

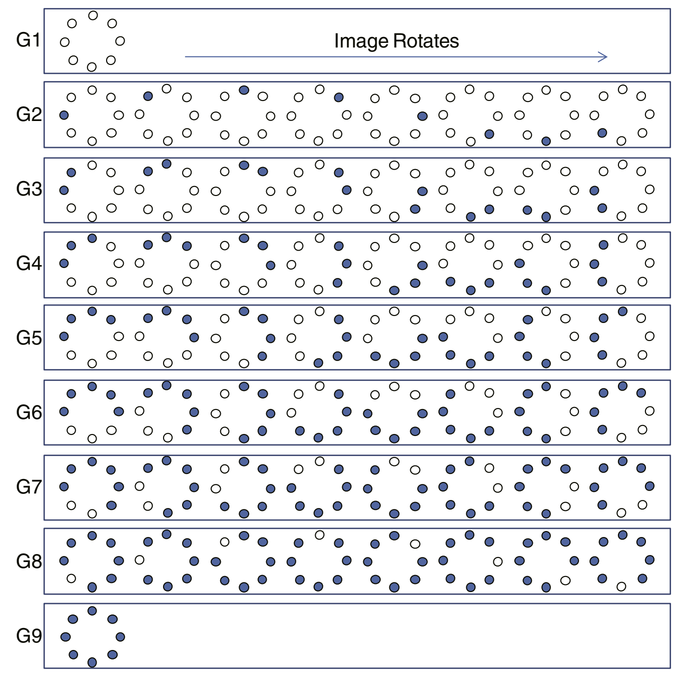

Fig. 2. All 58 uniform LBP patterns are divided into nine groups. The patterns in the same group have the same number of “1” and “0.”

2.2. LBP variants

After the LBP work, many LBP variants have been proposed and applied to different vision applications including face recognition, dynamic texture classification, scene classification, and medical image analysis. In [15], Tan et al. proposed a local ternary pattern (LTP) for face recognition. LTP is more insensitive to noise than the original LBP. To achieve rotation invariance, Ahonen et al. [16] proposed an effective LBP histogram fourier (LBPHF) feature. In [5], Guo et al. proposed an LBP variant (LBPV) descriptor to depict the local contrast information. To incorporate the sign and magnitude information, Guo et al. [4] introduced a completed LBP (CLBP) and demonstrated its superior performance in texture classification. Partly motivated by the CLBP, Zhao et al. [4] extended the LBPHF and introduced a LBPHF_S_M to fuse the sign and magnitude information. In [17], a novel linear configuration pattern (LCP) was introduced to explore multi-channel discriminative information of both the microscopic configuration and local features. Recently, there are several co-occurrence features introduced, including co-occurrence of adjacent LBP (CoALBP) [18], pairwise rotation invariant LBP (PRICoLBP) [9] and multi-scale joint encoding of LBP (MSJ-LBP) [19]. The CoALBP is sensitive to image rotation. And, as we will point out later, PRICoLBP and MSJ-LBP achieves rotation invariance by locally rotation invariant encoding approaches. Besides of abovementioned variants, there are still many other LBP variants including dominant LBP (DLBP) [20] and LBP difference (LBPD) [21].

Multi-scale strategy is widely used in the LBP and its variants including LBPV, CLBP, and LBPHF_S_M, and it usually boosts the classification performance of the descriptors. For instance, three scales (LBP(8, 1), LBP(16, 2), and LBP(24, 3)) [2] significantly improves the performance of the single scale for the texture classification task. Similar with the traditional LBP, most LBP variants (CLBP, LBPHF_S_M, LBPV, LCP) also use the multi-scale strategy and also obtain substantial improvement. The multi-scale strategy has been widely recognized as an indispensable means to achieve superior performance.

[1] https://www.dropbox.com/s/cl6lv8k0uk82dey/MCLBP.zip.