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Feature based local binary pattern for rotation invariant texture classification

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ABSTRACT

The local binary pattern (LBP) descriptor is widely used in texture analysis because of its computational simplicity and robustness to illumination changes. However, LBP has limitations to fully capture discriminative information since only the sign information of the difference vector in a local region is used. To enhance the performance of LBP, we propose a new descriptor for texture classification—feature based local binary pattern (FbLBP). In the proposed FbLBP, difference vector is decomposed into sign part and magnitude part, the sign part is described by conventional LBP, while the magnitude part is described by two features of the mean and the variance of the magnitude vector. The way we extract magnitude information in difference vector shows high complementarity to the sign part and less sensitive to illumination changes with a low dimensionality. Furthermore, an adaptive local threshold is used to convert these two features into binary codes. The proposed low dimensional FbLBP is very fast to construct and no parameters are required to tune for different kinds of databases. Experimental results on four representative texture databases of Outex, CUReT, UIUC, and XU_HR show that the proposed FbLBP achieves more than 10% improvement compared with conventional LBP and 1%–3% improvement compared with the best classification accuracy among other benchmarked state-of-the-art LBP variants.

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1. Introduction

Texture classification is an active research topic in many areas of pattern recognition and image processing in recent decades. The extraction of robust texture features is the primary task of texture classification. The main challenge of texture classification is to deal with the intra-class changes or variances, such as rotation, illumination, view point and scale. Consequently, some local descriptors are proposed to describe patches around properly chosen key points within the image, in which wavelets and pyramidal transformation are often used. These descriptors are naturally invariant to rotation, such as Scale Invariant Feature Transform (SIFT) (Lowe, 2004; Kang et al., 2011), Speeded-Up Robust Features (SURF) (Bay, Ess, Tuytelaars, & Van Gool, 2008). On the other hand, some descriptors are proposed to describe global features of an image in terms of texture, such as Local Binary Patterns (LBP) (Ojala, Maenpaa et al., 2002), Histogram of Oriented Gradients (HOG) (Junior, Delgado, Gonçalves, & Nunes, 2009). After local or global information in an image are extracted by feature extraction descriptors, they can be used for many application areas. Yuan, Sun, and Lv (2016) proposed to combine multi-scale local phase quantity (LPQ) descriptor with principal component analysis (PCA) for fingerprint liveness detection; Zhou et al. (2016) proposed to use two global features extracted from rotation invariant partitions to effectively detect image copy. Among different texture extraction descriptors, LBP has emerged as one of the most prominent texture descriptor, and a large number of LBP variants (Jin, Sheng, & Wood, 2015; Nanni, Lumini, & Brahnam, 2012; Pan, Wu, Li, & Zhou, 2017) have been developed to improve its robustness, discriminative power and applicability.

LBP has been applied to many application areas, such as texture recognition and edge detection. Compared with other texture descriptors, the LBP method has a low computational complexity and is invariant to monotonic illumination changes. Since Ojala's work (Ojala, Pietikäinen, & Mäenpää, 2002), numerous schemes which improved the LBP method have been proposed. The main direction of the improvements focuses on capturing more discriminative information and achieving stronger robustness. MRELBP (Liu et al., 2016) compares regional image medians rather than raw image intensities, which is different from the traditional LBP and many LBP variants. Guo, Wang, Zhou, and You (2016) proposed SSLBP and analyzed the scale space of LBP. Local Multiple Pattern (Zhu & Wang, 2012) extends original 2-valued LBP codes

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to multi-valued LMP codes to be more discriminative. Furthermore, LBP feature is easy to combine with other methods as well. In Local Vector Quantization Pattern (Pan, Fan, & Zhang, 2015), vector quantization is used to replace binary or multiple quantization to quantize the difference vector between the center pixel and its neighborhood pixels, and each different local structural pattern consequently matches a unique codeword index via searching a pattern codebook that is trained in advance. Furthermore, researches (Bruno et al., 2016; Nanni, Brahnam, & Lumini, 2010) applying LBP descriptor to different areas are also developed.

Although LBP and a lot of its variant methods achieve impressive classification accuracy on the representative databases, its working mechanism still needs investigations. In the viewpoint of LBP, a local region can be originally characterized by a P-dimensional difference vector d_P between the central pixel g_c and its neighbors g_p, where $d_P=[g_0-g_c, g_1-g_c, \dots, g_{P-1}-g_c]$ and P is the sampling number of neighbors. The LBP descriptor has limited capability to capture more discriminative information because only the sign of the difference vector d_P is used to represent the local region, the magnitude of difference vector d_P which also contains discriminative information is completely discarded. As a result, local regions with very different levels of grayscale difference may have the same LBP codes and lead to the misclassification of these different patterns.

To overcome this shortcoming of LBP, Guo, Zhang, and Zhang (2010) proposed the CLBP method, which combined three components of the difference vector d_P as: the sign descriptor (CLBP_S), the magnitude descriptor (CLBP_M) and the central pixel descriptor (CLBP_C). However, the CLBP scheme still has the following two disadvantages: (1) the CLBP_M is proposed to provide complementary information to CLBP_S (i.e., conventional LBP), but its dimensionality has the same size as CLBP_S, which results in a sharp increasement from $(P+2)$ to $(P+2)\times(P+2)$ in the size of histogram; (2) the complementarity between CLBP_M and CLBP_S still needs to be exploited. In the quantization process of the CLBP_M, the non-uniform pattern occupies the majority, which means only insufficient complementarity can be provided to CLBP_S. Later, a local descriptor named BRINT (Liu, Long, Fieguth, Lao, & Zhao, 2014) is proposed to overcome some limitations in CLBP. In BRINT, a method of arc-based averaging before binarization is introduced to make the number of final used neighbors fixed at eight so that the size of BRINT histogram becomes much lower than the size of CLBP histogram. Additionally, by using the rotation invariant LBP^{ri} (Pietikäinen, Ojala, & Xu, 2000) instead of the rotation invariant uniform LBP^{riu2} (Ojala, Maenpaa et al., 2002), BRINT avoids the problem that the non-uniform pattern occupies the majority in CLBP. However, on one hand, when extracting sign information, BRINT method of arc-based averaging is insufficient to describe the local region since the number of used neighbors is fixed to be eight; on the other hand, the way BRINT uses magnitude information is exactly the same as CLBP, which can be easily affected by rotation and illumination changes so that it still suffers the same limitations of CLBP_M.

Inspired by these analyses, we propose a new feature based local binary pattern (FbLBP) descriptor in this paper to overcome the disadvantages in CLBP and BRINT. In the FbLBP descriptor, first the sign of the difference vector d_P is described by conventional LBP, which fully preserves the advantages of uniform LBP. Then the magnitude information of the difference vector d_P is described by its two 1-dimensional features of the mean and the variance. These two features are functionally similar to CLBP_M but show better complementarity to LBP (i.e., the sign information) with much lower dimensionality. Moreover, the averaging operation in the process of calculating these two features can filter out the influence of rotation and illumination changes. Finally, the information of the central pixel g_c in the local region is also used in FbLBP. As a result, three FbLBP components are all in binary format so that they can be readily combined to construct the final feature histogram for texture classification.

The rest of this paper is organized as follows. Section 2 briefly reviews LBP and its related literatures. Section 3 presents the proposed FbLBP in detail. Section 4 discusses experimental results and Section 5 is the conclusion.

2. Brief review of related literature

2.1. Local binary pattern (LBP)

The original LBP code (Ojala, Pietikäinen et al., 2002) of a pixel is generated as follows:

$$LBP_{P,R}(g_c)=\sum_{p=0}^{P-1}s(g_p-g_c)2^p,\quad s(x)=\begin{cases}1 & x\ge 0\\ 0 & x<0\end{cases} \tag{1}$$

where g_c is the value of the central pixel, g_p (p = 0,..., P−1) represents the value of a neighbor pixel on a circle of radius R and P is the number of sampled neighbors. The neighbors that do not fall at the integer positions can be estimated by bilinear interpolation.

To achieve rotation invariance, a rotation invariant LBP descriptor LBP^{ri} (Pietikäinen et al., 2000) is proposed as follows:

$$LBP^{ri}_{P,R}=\min\{ROR(LBP_{P,R},i)\,|\,i=0,\dots,P-1\} \tag{2}$$

where $ROR(x,\ i)$ represents a circular bit-wise right shift function on the binary format vector $\boldsymbol{x}$ for i times and $LBP_{P,R}$ represents the P-*bit* LBP pattern.

On the other hand, Ojala, Maenpaa et al. (2002) proposed the uniform LBP because some certain patterns often occupied the majority among all the LBP patterns. They defined a uniformity parameter 'U' and the U value of an LBP pattern is defined as the number of bitwise changes in LBP pattern.

$$U(LBP_{P,R})=\left|s(g_{p-1}-g_c)-s(g_0-g_c)\right|+\sum_{p=1}^{P-1}s(g_p-g_c)-s(g_{p-1}-g_c) \tag{3}$$

If $U\le 2$, the LBP patterns are assigned to the uniform patterns; Otherwise, the LBP patterns are classified as the non-uniform pattern.

To achieve rotation invariance, the rotation invariant uniform LBP is defined as:

$$LBP^{riu2}_{P,R}=\begin{cases}\sum_{p=0}^{P-1}s(g_p-g_c), & if\,U(LBP_{P,R})\le 2\\ P+1, & otherwise\end{cases} \tag{4}$$

The rotation invariant uniform patterns defined in Eq. (4) are usually called LBP^{riu2}. Because of the usefulness for rotation invariant to texture classification, the conventional LBP in the following context refers to the LBP^{riu2}.

2.2. LBP variants

In fact, LBP and its variants have a close relationship with grey-level differences (Weszka, Dyer, & Rosenfeld, 1976), since they all focus on local property values and characterize different grey-level distributions among different pixels in this local area. Grey-level differences (GLD) uses the probability distribution of the absolute difference between the grey levels of two predefined pixels.

Basically, these diverse texture descriptors, including GLD, LBP and its variants, all belong to a class of methods known as Histograms of Equivalent Patterns (Bianconi & Fernández, 2014; Fernández, Álvarez, & Bianconi, 2013), which is based on partitioning

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