Exploring Cross-Channel Texture Correlation for Color Texture Classification

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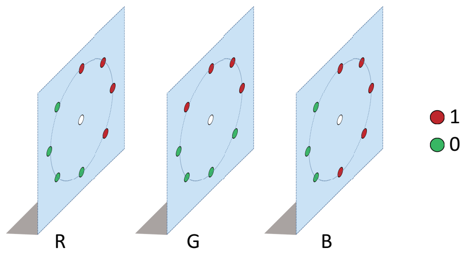

Figure 1: An illustration of LBPs in RGB channels.

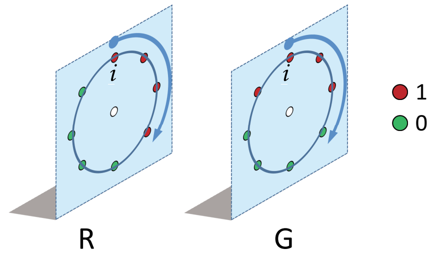

Figure 2: An illustration of encoding strategy between two different color channels.

Color and Texture are two important aspects of natural images. It is widely recognized that they provide strong complementary cues to each other in a lot of computer vision applications, such as object recognition, flower recognition, texture classification, material recognition, content-based image retrieval, color texture segmentation and many more.

Recently, Local Binary Pattern (LBP) descriptor [4] and its variants [1, 2, 5, 7] have been widely applied on texture relevant tasks due to their computational efficiency and great texture discriminative ability. In [5], Timo et al. systematically introduced the LBP operator and its several variants including uniform LBP and rotation invariant LBP. Since then, LBP has been widely applied to a lot of tasks, such as face recognition, image retrieval, and many more [6]. Recently, in [1], Zhenhua et al. proposed a completed LBP operator, which further enriches the original LBP feature.

The simplest and most direct method to incorporate color cue to the texture classification task is to extract LBP histograms from each color channel ,and then concatenate the histograms into a final image representation. In the literature, this method has been used in several works [3, 8]. In [3], Maenpaa et al. used color LBPs (different color space) for texture classification, and in [8], Zhu et al. proposed to use color LBPs for object recognition.

However, the above color and texture fusing approach approach just treats each channel independently, and ignores the cross-channel texture correlation information. In fact, there exists strong correlation between texture patterns of different color channels. Such a correlation reflects the common character and the difference between patterns from different channels. Fig. 1 shows a typical structure in RGB color channels. The LBP sequences in RGB channels are greatly correlative to each other. Encoding the correlation effectively can greatly boost the discriminative ability of the feature.

In this paper, we propose a novel method to encode the cross-channel texture correlation to conduct color texture classification task. Firstly, we quantitatively study the texture correlation between different color channels using LBP as texture descriptor and using the Shannon's information entropy as correlation measurement. Based on the study, we find that (R, G) channel pair have stronger texture correlation than (R, B) and (G, B) channel pairs. Secondly, we propose a novel approach to encode the cross-channel texture correlation. The proposed method captures well the relative variance of the texture patterns between different channels. In practice, we divide three color channels into three pairs and encode any one pair each time. The histograms of three pairs are finally concatenated into a final image representation. The proposed method is computationally efficient and robust to image rotation. Its computational cost is similar to the classical multi-channel color LBP. Meanwhile, the novel encoding strategy of the proposed method can guarantee rotation invariance.

Encoding Strategy: Take (R,G) channels as an example, as shown in Fig. 2, the Cross-Channel LBP (*CCLBP*) can be defined as follows:

$$CCLBP_{R,G}(n,r|c_R,c_G) = [LBP_R^{riu}(n,r|c_R), LBP_G^{u}(n,r|c_G,i)]_{co}, \tag{1}$$

Where

$$i = \arg\max_i \{ROR(LBP_R(n,r,|c_R),i) \mid i = 0,1,....,P1-1\}, \tag{2}$$

According to Eq. 1, the dimension of joint encoding of two channels is $10 \times 59 = 590$. In this paper, we use dense sampling to calculate the histogram. For each pixel in an image, we accumulate their joint patterns into the corresponding bin of histogram. Finally, we normalize the histogram feature with L_1 norm. The histograms of (R, B) and (G, B) can be built similarly. Thus, by concatenating these histograms of pairs of crossing-channel features, we obtain the whole *CCLBP* representation for the image as:

$$CCLBP_{R,G,B} = [CCLBP_{R,G}, CCLBP_{R,B}, CCLBP_{G,B}]. \tag{3}$$

in which the dimension of the $CCLBP_{R,G,B}$ is $590 \times 3 = 1770$.

[1] Zhenhua Guo, Lei Zhang, and David Zhang. A completed modeling of local binary pattern operator for texture classification. *TIP*, 19(6): 1657–1663, 2010.

[2] Zhenhua Guo, Lei Zhang, and David Zhang. Rotation invariant texture classification using lbp variance (lbpv) with global matching. *Pattern Recognition*, 43(3):706–719, 2010.

[3] Topi Mäenpää and Matti Pietikäinen. Classification with color and texture: jointly or separately? *Pattern Recognition*, 37(8):1629–1640, 2004.

[4] Timo Ojala, Matti Pietikäinen, and David Harwood. A comparative study of texture measures with classification based on featured distributions. *Pattern recognition*, 29(1):51–59, 1996.

[5] Timo Ojala, Matti Pietikainen, and Topi Maenpaa. Multiresolution gray-scale and rotation invariant texture classification with local binary patterns. *PAMI*, 24(7):971–987, 2002.

[6] M Pietikäinen, A Hadid, G Zhao, T Ahonen, M Pietikäinen, A Hadid, G Zhao, and T Ahonen. Computer vision using local binary patterns. 2011.

[7] Xianbiao Qi, Rong Xiao, Jun Guo, and Lei Zhang. Pairwise rotation invariant co-occurrence local binary pattern. In *ECCV*, pages 158–171. Springer, 2012.

[8] Chao Zhu, C-E Bichot, and Liming Chen. Multi-scale color local binary patterns for visual object classes recognition. In *ICPR*, pages 3065–3068, 2010.