COLOR TEXTURE REPRESENTATION USING CIRCULAR-PROCESSING BASED HUE-LBP FOR HISTO-PATHOLOGY IMAGE ANALYSIS

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ABSTRACT

Texture is considered one of most significant information sources in histo-pathology image analysis. To take advantage of information on color texture in digital histo-pathology, this work analyzes inherent characteristics of the hue component in the cylindrical color space, and introduces an effective color texture descriptor based on the LBP paradigm. Unlike existing LBP variants designed for linear data, the proposed descriptor, namely Hue-LBP, addresses the angular and periodic nature of hue and shows that color variation in the hue channel can be quantified by an angular variable in the range of $[0, 180]$. By introducing the concept of color similarity as a metric to measure color variation, we obtain a histogram to describe local color texture patterns. Experimentation on histo-pathology image classification suggests that the proposed Hue-LBP is discriminative as it is capable of describing texture information conveyed by the hue components.

Index Terms— Texture description, Hue-LBP, circular processing, histo-pathology image analysis

1. INTRODUCTION

Histo-pathology image analysis is a new research realm that exploits color image processing algorithms to achieve intelligent pathology image understanding. Different from other medical images (such as X-ray imaging or MRI imaging) that deliver medical information by image intensities, histo-pathology images are color in nature. Since chemical staining highlights histological components of interest by counter-color chemical dyes in biopsy sample preparation, color spatial distributions in the corresponding histo-pathology image are strong indicators of spatial organization of tissue substances. Hence, some efforts have been made to study color textures in histo-pathology image analysis. For instance, in [1, 2], the authors compared grayscale texture features to its color-version texture descriptors in histo-pathology image classification, and concluded that color texture descriptors improve classification performance when limited appearance variation resulting from the disagreement of illumination conditions existed in histo-pathology images. Though appearance variation introduced by different illumination conditions is a challenge in digital histo-pathology [3], recent work on color normalization for histo-pathology images [4] can be used to mitigate effects of such appearance variation on subsequent quantitative analysis. Based on these previous works, we believe that effective color texture descriptors would contribute to digital histo-pathology image analysis.

Note that most texture analysis tools are proposed for grayscale images using scalar processing, it is a non-trivial task to extend it to color images. To exploit color information for accurate texture analysis, a straightforward method is to apply grayscale texture features to each channel in a color spaces and then concatenate the obtained features together [1]. To take the correlation between color channels into consideration, opponent color (OC) texture description method [5] which computed 6 texture features from pairs of color channels was proposed. To obtain a compact color texture descriptor, the work [6] applied the LBP operator to the hue channel and illustrated its good performance on the PASCAL visual object classes challenge 2007 image benchmark. Recently, vector processing based method to extract color texture features was designed for face recognition [7, 8], where LBP was extracted from the color magnitude and color angular domains individually.

Among the color texture research, the work that computes LBP from the hue channel interests us. In the HSV domain, chromatic information is separated from image luma [9] and mainly delivered by the hue component. Therefore, extracting LBP from image hue components leads to a compact color texture descriptor. However, it should be noted that hue is a circular color descriptor and ignoring its non-linear property in analysis may introduce error. Hence, in this paper, we analyze characteristics of the hue component in the cylindrical color space, and propose a novel hue-LBP (HLBP) descriptor. Unlike existing texture analysis algorithms being scalar processing, the proposed Hue-LBP quantifies color change in the hue component using circular processing and generates HLBP based on color similarity quantification. To investigate the descriptive power of the proposed color descriptor in histo-pathology image analysis, in experimentation, we extract HLBP and classical LBP from the hue channels, and compare their performance in glomerulus image classification, concluding that the introduced descriptor is more discriminative.

The rest of this paper is organized as follows. As the construction of the proposed Hue-LBP follows the classical LBP paradigm, Section 2 briefly reviews the LBP algorithm. In Section 3, the circular nature of hue is analyzed, followed by the specification of Hue-LBP. Performance evaluations are discussed in Section 4, followed by conclusions in Section 5.

2. BACKGROUND

Due to the computational efficiency and discriminative power of LBP, it is widely adopted to quantify texture patterns in image analysis. The proposed feature in this paper can be considered as a variant of LBP particularly designed for circular data such as the hue component. Hence, this section reviews the LBP paradigm concisely before the specification of Hue-LBP.

LBP describes the local texture at an image pixel (x, y) by thresholding its neighborhood using intensity value $I(x, y)$, where the neighborhood is defined by P equally spaced pixels on a circle of radius R. In specific, a neighbor pixel is defined by $N_p(x, y) = (x + Rcos(2p\pi/P), y - Rsin(2p\pi/P))$ for $p \in [0, P-1]$. If $N_p(x, y)$ is not on integer coordinates, intensity of the neighbor pixel $I(N_p(x, y))$ is computed through interpolation. The LBP index is then obtained by

$$LBP_{P,R}(x, y) = \sum_{p=0}^{P-1} s(I(x, y) - I(N_p(x, y))) \times 2^p, \quad (1)$$

where $s(z) = 1$ for $z \geq 0$; otherwise, $s(z) = 0$. By accumulating LBP indexes in a histogram $hist_I$, a vector with length 2^P is obtained and used as features, where the i^{th} bin of the histogram is defined as follows.

$$hist_I(i) = \sum_{x,y} \delta(i, LBP_{P,R}(x, y)), \quad (2)$$

where $\delta(\cdot)$ is the Kronecker delta. Though the LBP descriptor is simple, it is invariant to grayscale intensity change [10] and very discriminative for textures. Later, various LBP variants are proposed to improve the original LBP algorithm in terms of rotation invariance [10, 11], soft histogram [12], and dominant LBP descriptors [13].

3. HUE-LBP BASED ON CIRCULAR PROCESSING

Grayscale texture features describe the spatial arrangement of image intensity. Particularly in LBP, local intensity change patterns are summarized based on linear signal order. Since hue is a periodic signal on the unit circle, linear order is ill-defined for hue. To quantify color texture within an image, we process hue signals using circular processing and introduce the Hue-LBP descriptor which aims to describe local color variation patterns in this section.

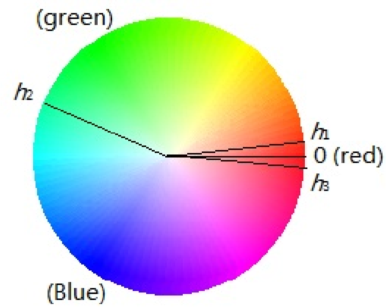

Fig. 1. Hue is an angular measurement on the unit circle of the chromatic plane. Color h_1 and h_3 are similar, while h_2 represents a very different color.

3.1. Angular Nature of Hue

Hue is an efficient color feature, independent of image luma attribute. In the cylindrical color spaces, for instance, the HSV color space, hue is an angular quantity on the unit chromatic circle, with a period of 360. That is, hue values $h+360k$ for $k \in Z$ represent the same color. For illustration, Figure 1 depicts the hue circle, where the hue value equaling 0 corresponds to red. As shown in the figure, color on the chromatic circle follows the distribution that similar colors have similar hue values, residing closely. For instance, color h_1 and h_3 in Figure 1 are close and belong to the red region, while h_2 is located far from them on the circle and represents a very different color.

Note, though quantification in a scalar system, such as image intensity, can be used to compare and order signals, in the hue circle, the hue value is a quantitative description of colors and cannot be used for color ordering. For specific, scalar variables reside along the real axis, where the number on the left is always smaller then the number on the right. Hence when we travel along the real axis from n_0, we will depart from it and can never return back to n_0. However, if we travel along the hue circle from h_0, we always return back to the same color since $h_0 = h_0 + 360k$ for $k \in Z$. Hence, it is problematic to say $h_i < h_i + \Delta$ for $\Delta > 0$ on the chromatic plane.

Since color order based on hue values is ill-defined, applying LBP on image hue components based on hue values is problematic. This is because the basic operator of LBP is signal order/comparison, as described in (1). Therefore, to accurately quantify color texture patterns in the hue component, new color texture features that addresses the periodic and angular nature of hue are needed.

3.2. Angular Similarity Based HLBP

Color texture describes the spatial color arrangement in an image. As color transition on the hue circle is very smooth, a very small amount of change in hue values may not be observed by human. Motivated by this observation, we propose to use color similarity, rather than color order, as the basic operator to quantify color textures.

Specifically, to address the angular nature of the hue component when describing local color variation, color difference between h_i and h_j is quantified by an angular quantity Δh such that

$$\|h_i - h_j\|^2 = \|h_i\|^2 + \|h_j\|^2 - 2\|h_i\|\|h_j\| \cos(\Delta h), \quad (3)$$

where $\|\cdot\|$ is the vector norm. As hue resides on the unit circle, $\|h_i\| = \|h_j\| = 1$. Hence, $\|h_i - h_j\|^2 = 2 - 2\cos(\Delta h)$. In circular computation, $\|h_i - h_j\|^2 = [\sin(h_i) - \sin(h_j)]^2 + [\cos(h_i) - \cos(h_j)]^2$. After trigonometric derivation, it is not hard to obtain $\|h_i - h_j\|^2 = 2 - 2\cos(h_i - h_j)$. Hence,

$$\cos(\Delta h) = \cos(h_i - h_j). \quad (4)$$

Note, as hue is an angular variable, color difference Δh should be measured by the acute angle formed by h_i and h_j, rather than the value of $h_i - h_j$. Hence, when colors are separated apart by 180 on the chromatic plane, it results in the largest color difference. For instance, h_1 and h_3 in Fig. 1 denote two colors close to red. The color difference should be measured by the acute angle of $h_1 + 360 - h_3$, rather than the value of $h_3 - h_1$. That is, color difference has a constraint that $\Delta h \in [0, 180]$. Therefore, with $h_i \in [0, 360)$ and $h_j \in [0, 360)$, Δh is defined as

$$\Delta h = \begin{cases} |h_i - h_j| & \text{if } |h_i - h_j| \leq 180 \\ 360 - |h_i - h_j| & \text{otherwise} \end{cases}, \quad (5)$$

where $|\cdot|$ is the operation of obtaining the absolute value.

In the LBP computation, intensity difference is either negative or positive (plus zero) and represented by either 0 or 1. However in the hue channel, as color order is undefined and $\Delta h \in [0, 180]$, the operation $s(\Delta h)$ in (1) is always 1, which does not deliver any information on texture patterns. Therefore, we introduce a threshold $th \in [0, 180]$ in the proposed Hue-LBP descriptor, and propose to use color similarity as a metric to characterize local color variations. In specific, when $\Delta h - th > 0$, we consider the two colors are different; Otherwise, the two colors are similar. Hence, by casting the angular similarity comparison into the LBP paradigm, our Hue-LBP can be formulated as follows.

$$HLBP_{P,R}^{th}(x, y) = \sum_{p=0}^{P-1} s(\Delta h - th) \times 2^p. \quad (6)$$

Finally, the color texture features are summarized by a histogram $hist_I^{th}$, where the i^{th} bin is

$$hist_I^{th}(i) = \sum_{x,y} \delta(i, HLBP_{P,R}^{th}(x, y)). \quad (7)$$

Note that in histo-pathology image analysis, rotation invariance and uniformity are very important properties for texture description. Hence, for the proposed descriptor $HLBP_{P,R}^{th}(x, y)$, we follow the mapping rule of the rotation-invariant uniform LBP, $LBP_{P,R}^{riu}$ [10], and obtain a rotation-invariant uniform feature $HLBP_{P,R}^{th,riu}(x, y)$.

Since the proposed Hue-LBP only considers color variation patterns, no texture information associated with image luma component is included. To obtain a complete color texture patterns, we concatenate HLBP with LBP extracted from the value component in the HSV color space. Given a color histo-pathology image represented in the HSV domain, $I = [I^h, I^s, I^v]$, the resulting texture feature vector is thus generated by $Hf_I^{th} = hist_{I^h}^{th} \oplus hist_{I^v}$, where $\oplus$ is the concatenation operator[1].

4. EXPERIMENTATION AND DISCUSSIONS

Tow experiments are designed to evaluate the new descriptor, Hue-LBP. The first experiment evaluates the descriptive power of texture features which is classification-independent. The other one is classification of histo-pathology images based on texture features. All simulations run on Matlab.

In this study, we use the GlomDB glomeruli dataset [2], published for color and texture descriptor evaluation, as evaluation images. The GlomDB dataset consists of 1976 16-by-16 non-overlapping square patches selected from 15 kidney biopsies stained following the Masson's trichrome protocol in the same hospital. Among the 1976 patches, half images correspond to kidney glomeruli and the other half contain other tissue substances in kidney biopsies.

4.1. Descriptive Power of HLBP

Evaluation of the proposed color texture feature is first based on a classification-independent experiment.

Experimental Design: The new descriptor $HLBP_{P,R}^{th,riu}$ is computed from the hue channel of each GlomDB image, where we set $th = 36, P = 8, R = 1$. Then the discriminant power of Hue-LBP associated with glomerulus and non-glomerulus patches is examined qualitatively. In this experiment, we believe that a descriptor has large discriminant power if the feature sets between glomerulus and non-glomerulus images are more separable. For comparison, this experiment is also performed on the classical LBP descriptor obtained by (1) and (2) extracted from the Hue channel.

Results and Discussion: Since dimensions of $LBP_{8,1}^{riu}$ and $HLBP_{8,1}^{36,riu}$ extracted from the hue channel are 10, to visualize their discriminant powers, we use PCA to reduce the feature dimension to 2, and depict the projected feature sets in Fig. 2, where the axes of the plots correspond to the two dominant eigenvectors found by PCA, and a red $*$ and a

[1]The texture features from the saturation components are not included because in hito-pathology images, less histological information conveyed by saturation.

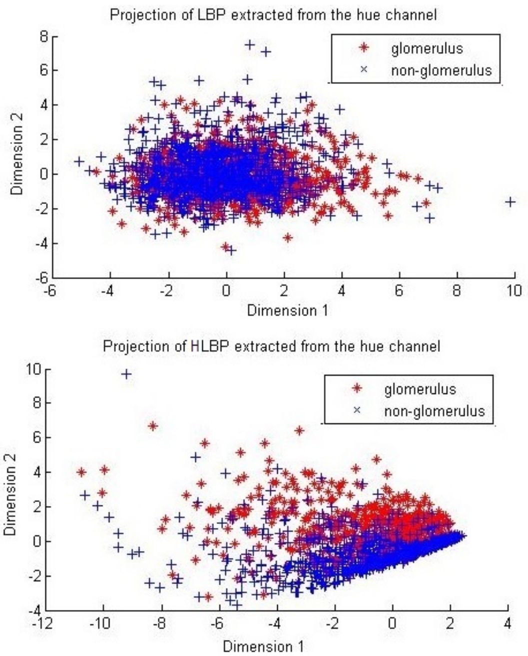

Fig. 2. Texture descriptor $LBP_{8,1}^{riu}$ and $HLBP_{8,1}^{36,riu}$ in the hue channel are projected into 2-dimensional subspaces by PCA to visualize their discriminative powers. In the figure, a red $*$ represents a glomerulus patch, and a blue $\times$ corresponds to a non-glomerulus image.

blue $\times$ represent a glomerulus patch and a non-glomerulus image, respectively. Texture features of glomerulus and non-glomerulus images described by $LBP_{8,1}^{riu}$ that is depicted in the top diagram mix together, whereas features of glomerulus and non-glomerulus patches representd by $HLBP_{8,1}^{36,riu}$ in the lower plot are more separable. This observation suggests that the proposed circular processing based Hue-LBP is more descriptive for the GlomDB image set because angular nature of hue is carefully addressed in HLBP.

4.2. Glomeruli Image Classification

In the second experiment, we evaluate Hue-LBP in terms of binary classification over the GlomDB image set.

Experimental Design: The 10-fold cross validation methodology is adopted in this experiment, where the entire GlomDB image set is split into two parts, with 1/10 as training cases, and 9/10 as testing images. To avoid data drift in evaluation, both training and testing sets maintain the same proportion of glomerulus images as that the original dataset has. After training a linear classifier based on the dominate 10 features selected by PCA from the 1/10 images, the testing images are classified individually based on extracted features. In this experiment, four different sets of texture features are evaluated, which include $LBP_{8,1}^{riu}$ and $HLBP_{8,1}^{36,riu}$ in the hue channel only, and $f_I = hist_{I^h}^{th} \oplus hist_{I^v}$ and $Hf_I^{th} = hist_{I^h}^{th} \oplus hist_{I^v}$ from the value and hue components in the HSV domain.

Table 1. Statistics (Mean (std)) of glomerulus image classification over the GlomDB dataset

Feature	Dim	ACC	AUC
$LBP_{8,1}^{riu}$	10	0.559 (0.035)	0.606 (0.038)
$HLBP_{8,1}^{36,riu}$	10	0.671 (0.028)	0.716 (0.036)
f_I	20	0.673 (0.032)	0.733 (0.033)
Hf_I^{th}	20	0.743 (0.030)	0.816 (0.028)

The agreements between groundtruth and classification results are estimated using two metrics, which are classification accuracy (ACC) and the area under the ROC curve (AUC). Both ACC and AUC are in the range of $[0, 1]$, and large values indicate better classification. The 10-fold cross validation process is repeated 5 times and the 50 performance indexes are summarized for each feature set.

Results and Discussion: Table 1 lists the statistics of the classification results using different sets of texture features over the GlomDB dataset. We obtain two observations in this experiment. First, the first two rows in the table show statistics of glomberulus classification using texture features extracted from the hue channel only. With similar computational complexity, $HLBP_{8,1}^{36,riu}$ greatly improves classification performance compared to $LBP_{8,1}^{riu}$. This actually can be inferred from our observations in the previous experiment. Second, when texture information in the value channel in the HSV color space is included in feature sets, classification performances are boosted. This suggests that texture features extracted from image hue component and the luma component are complementary.

5. CONCLUSION

Color cues due to chemical staining is considered a very important information source in histo-pathology image analysis. However, directly applying classical linear texture descriptors to the hue component of an image may introduce analysis error. To take advantage of color cues conveyed by image hue components in histo-pathology image, this paper analyzes characteristics of the hue component in the HSV color space, and introduces a descriptive color texture feature, Hue-LBP, based on the paradigm of LBP. Particularly, the novel descriptor takes into account the circular and periodic nature of hue, and uses an angular variable to quantify color variation. To represent local color change within a neighborhood, we propose to use the concept of color similarity, rather than signal order which is ill-defined for hue, to generate the LBP-equivalent histogram. Experimentation on glomerulus images suggests the superiority of the introduced descriptor in terms of discriminative power in the hue component.

6. REFERENCES

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