Local Texture Descriptors for Color Texture Classification Under Varying Illumination

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***Abstract*—Color texture classification under varying illumination remains a challenge in the field of computer vision, and it greatly relies on the efficiency of the feature descriptors. The aim of the thesis is to improve the classification of color texture acquired with varying illumination sources by improving the description power of feature descriptors. We propose three new color texture descriptors, namely: the Opponent Color Local Mapped Pattern (OCLMP), which combines a local methodology (LMP) with the opponent-colors theory; the Color Intensity Local Mapped Pattern (CILMP), which extracts color and texture information jointly, in a multi-resolution fashion and the Extended Color Local Mapped Pattern (ECLMP), which applies two operators to extract color and texture information jointly as well. As the proposed methods are based on the LMP algorithm, they are parametric functions. Finding the optimal set of parameters for the descriptor can be a cumbersome task. Therefore, this work adopts genetic algorithms to automatically adjust the parameters. The methods were assessed using two texture data sets acquired under varying illumination sources: RawFooT (Raw Food Texture Database), and the KTH-TIPS-2b (Textures under varying Illumination, Pose and Scale Database). The experimental results show that the proposed descriptors are more robust to variations to the illumination source than other methods found in the literature. The improvement on the accuracy was higher than 15% in the RawFoot data set, and higher than 4% in the KTH-TIPS-2b data set.**

I. Introduction

In general, image segmentation and feature extraction are based on three image properties: shape, color and texture. These three properties are commonly treated independently when a scene or an object is described in the form of a feature vector. The shape defines the outline patterns of the image, and color refers to the pixel intensities at each channel. Texture is perhaps the most controversial property and is not easily defined. It represents how the pixels are spatially arranged in an image, and it encompasses the concept of shape and color itself.

Texture analysis in digital images plays an important role in many applications, such as robotics [1], biometrics [2], medicine [3], remote sensing [4], among others.

Although texture is intuitively easy to comprehend, the literature does not provide a concise and exact definition of the term. Tuceryan and Jain (1993) define image texture as the function that describes the spatial distribution of the pixel intensities [5]. According to Coggins (1983), texture is a primitive pattern which is repeated over a region, which is much larger compared to the original primitive pattern [6]. Haralick, et. al (1973) used uniformity, density, roughness, regularity, intensity and other coefficients to define texture [7].

Texture provides relevant characteristics about the pixel spatial organization over a given region, which is a requirement to successfully recognize, describe and classify images.

In digital images, texture can be defined through pixel intensity (luminance) and pixel color (chrominance) [8]. A great portion of the texture descriptors presented in the literature are based exclusively on the luminance information, i.e., only the pixel intensity is considered by the description process. Methods that incorporate chrominance information to the texture description are known as Color Texture. This relatively new approach has been investigated by many groups and has shown to improve the description capability of the conventional texture descriptors [9]–[14].

Texture and color information can be extracted from an image and combined into a feature vector in different ways. Palm (2004) classifies the different approaches into three groups: parallel, sequential and integrative [10]. In the parallel approach, the texture is described locally considering the relation of a given pixel with its neighboring pixels, and only the global color properties are considered, ignoring its local distribution. In the sequential approach, a colored image is quantized to generate a single color channel, and the single channel is then treated as a grayscale texture. The integrative methods process color and texture jointly, considering each color channel separately or combined.

Some of the existing texture descriptors, such as the Local Binary Pattern (LBP) and its variations [15], [16], and the Gabor filters [17], may be applied to color textures. The descriptor is applied to each color channel separately, and the resulting feature vectors are concatenated into a color texture descriptor [9]. However, there are dedicated methods, designed specifically to describe colored textures [13], [14], [18], [19].

Maenpaa and Pietikainen (2004) compared the performance of a number of color and grayscale texture descriptors. Three datasets were considered in the experiments. Furthermore, a range of color spaces were tested. The study indicated that when the illumination is constant, all methods yield similar performance with the color texture descriptors performing slightly better than the average. However, in the presence of changing illumination the grayscale methods performed better

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[9].

The importance of color in texture classification was also carefully investigated by Bianconi et. al (2011). They proposed a new approach to classify the existing descriptors and assessed the performance of colored textures in a popular dataset, namely the OUTEX 13 [16], which also features textures with changes in orientation. The results showed that color indeed improves the performance of texture descriptors. However, in this study the robustness of the descriptors to changes in illumination was not tested [20].

Due to its simplicity and flexibility, the Local Binary Pattern (LBP) is one of the most popular texture descriptor available in the literature [15]. In the recent years, many works explored the application of LBP and new variations were proposed. Ojala, et. al (2002) proposed an extension of the LBP methodology to improve its robustness to changes in texture rotation. However, as shown by [9], the performance of the LBP descriptor is negatively impacted by changes in the illumination.

Indeed, one of the main challenges in color texture description is the robustness to changes in intensity, direction and temperature of the illumination, due to the impact of these changes to the texture color. Figure 1 shows the same texture captured under different illumination settings.

(a) Illumination 1 (b) Illumination 2 (c) Illumination 3

Fig. 1. The same texture under three different illumination sources.

One alternative to solve the issues that arise from changes in illumination is to apply color normalization before the feature extraction process, therefore minimizing the effect of the illumination to the sample color [19], [21]–[25]. However, as presented by [25], the normalization step is costly and only effective in specific scenarios.

A new local texture descriptor named Local Fuzzy Pattern (LFP), based on the *fuzzy* theory, was proposed in [26]. The LFP methodology was extended to the Local Mapped Patterns (LMP) in [27]. The LMP descriptor considers the difference between the intensity of the central pixel and each of its neighboring pixels in a given neighborhood. The differences are mapped into a bin of a histogram through a mapping function.

Due to the descriptive capabilities of the LMP methodology, the Ph.D. thesis proposes the investigation and development of LMP-based methodologies for the description of color textures, especially in the cases with changes in illumination.

A. Objectives and Contributions

The main objective of the thesis is the development of new LMP-based texture descriptors, dedicated to the description of color textures under varying illumination. The contributions of the thesis include:

- The development of the descriptor *Opponent Color Local Mapped Pattern* (OCLMP), which integrates the LMP approach to the opponent-colors theory. The opponent-colors theory is inspired by the human visual system;
- The development of the descriptor *Color Intensity Local Mapped Pattern* (CILMP), which explores color textures by comparing the magnitude of the color vectors within the RGB cube. This descriptor combines luminance and chrominance information in a multi-resolution fashion, considering the relation between the central pixel of a neighborhood and its neighboring pixels;
- The development of the descriptor *Extended Color Local Mapped Pattern* (ECLMP), which extends the same theory as used in the CILMP descriptor by comparing the relation between pixels at different resolutions.

II. Methods

A. Opponent Color Local Mapped Pattern

The first descriptor proposed by the thesis was the OCLMP. The method was inspired by the OCLBP descriptor [9], and combines the LMP approach with the opponent-colors theory [28]. As presented by [25], the OCLBP reports high performance describing color texture under varying illumination.

The representation of color texture using opponent-colors consider the pairs of colors within the specific color space. For example, for textures described by the RGB color space, the opponent-colors are: R-G, R-B, G-R, G-B, B-R and B-G. As highlighted by [9], the symmetric pairs, such as R-B and B-R, are redundant and only one of them is required during the texture description process.

The feature extraction is performed considering the relation between the central pixel of a neighborhood located in one of the color channels, and the neighboring pixels from an opponent-color channel.

The feature vector is built using the S-LMP circular sampling methodology [29]. In addition to opponent-color features, the method also estimates the S-LMP code from each color channel separately. All histograms are concatenated to form the feature vector. It is important to highlight that the proposed method generates a total of six histograms. The mapping function may be optimized individually for each of the histograms.

B. Color Intensity Local Mapped Pattern

In CILMP, the texture information is extracted from the image luminance by the S-LMP descriptor [29]. To get a multiresolution analysis, the descriptor is applied using different neighborhood configurations. The obtained histograms from each neighborhood configuration are concatenated to form the CILMP texture feature vector.

For the extraction of color information we propose a novel approach based on the magnitude of the color vectors inside the RGB cube. On a three-dimensional color space, each axis represents a channel, and therefore each color can be

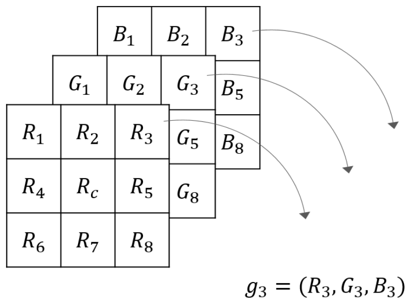


Fig. 2. Local Pattern 3×3 of an RGB image.

represented as a point inside the 3-D space. For example, in the RGB color space, a color is characterized by its primary components red, green and blue [30]. A local pattern of a color texture is a three-dimensional matrix where each pixel is described by three coordinates $g_i = (R_i, G_i, B_i)$ as shown in Figure 2.

To extend the S-LMP descriptor for color images, the difference between the squared magnitudes of vectors in the RGB space is used as input of the sigmoid function

$$f_{g_p} = \frac{1}{1 + \exp\left(\frac{-(||g_p||^2 - ||g_c||^2)}{\beta}\right)}, \quad (1)$$

where β is the steepness of the mapping function, g_c is the central pixel of the local pattern and g_p is a neighbor of g_c. Symmetric circular neighborhoods are used to allow a multiresolution analysis. The patterns are mapped to a histogram bin h_b. Figure 3 shows an RGB texture and its S-LMP map obtained considering the sigmoid function presented by Eq. 1, eight neighbors and radius equal to two.

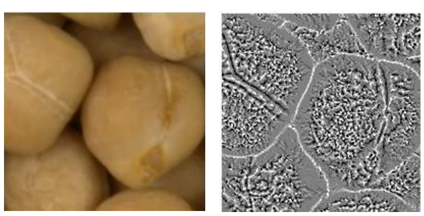


Fig. 3. Example of an RGB texture and its S-LMP map.

We apply the descriptor to color textures using different neighborhood configurations. The obtained histograms are concatenated to the texture histograms provided by the S-LMP, forming the CILMP feature vector.

Figure 4 shows the multiresolution analysis performed by the CILMP: different radius and number of neighbors are used to extract texture information from the luminance map and color information from the RGB channels. Note that, for example, the neighborhood $(P, R) = (24, 5)$ just considers the pixel values which are distant five positions from the central pixel. Combining different neighborhood resolutions allows the descriptor to extract information from a larger area, including more features in the feature vector.

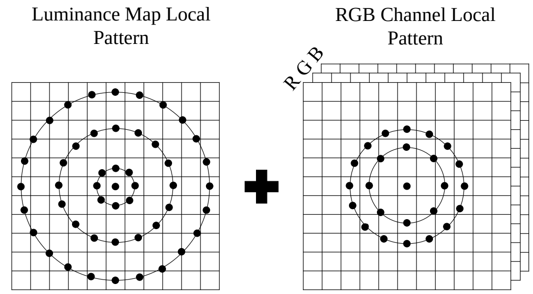


Fig. 4. Example of a multiresolution analysis by the CILMP using five configurations: $(8,1)+(16,3)+(24,5)$ for the luminance map and $(8,2)+(16,3)$ for the RGB channels.

C. Extended Color Local Mapped Pattern

The Extended Color Local Mapped Pattern (ECLMP) is a parametric LMP-based descriptor [27] designed to be robust to changes in the scene illumination. The proposed descriptor uses two operators, $ECLMP_c$ and $ECLMP_r$, to extract color-texture and texture information from the image, respectively. The $ECLMP_c$ explores a novel approach to extract information from neighboring pixels: the pixels in a circular neighborhood are compared to the neighborhood pixel average, including the central pixel. The $ECLMP_r$ captures the relationship between pixels from different neighboring resolutions of an image. The texture information is extracted from the image luminance and the color-texture information is incorporated using the magnitude of the color vectors inside the RGB cube.

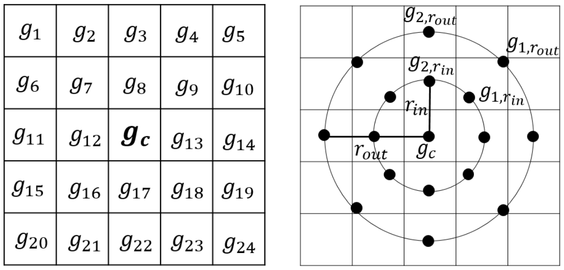
In this subsection, we first explain how the ECLMP incorporates texture information from the image luminance using the $ECLMP_c$ and $ECLMP_r$ operators. Then, we extend the method for color textures in the RGB space. Finally, we present how the ECLMP combines both texture and color-texture information in a multiresolution fashion.

1) Texture Information Extraction: Consider a 5×5 local pattern, taken from an image as shown in Figure 5. The ECLMP extracts information from such local pattern by considering the luminance values located in concentric circular neighborhoods. Each neighborhood is defined by P pixels $g_{p,r}$ ($p = 1, ..., P$) equally spaced in a circle of radius $r, r > 0$. Assuming the central pixel g_c is located at $(x, y) = (0, 0)$, the coordinates of the neighboring pixels $g_{p,r}$ are given by Eq. (2). When the pixel coordinates are not integer values, the pixel gray levels are estimated through interpolation, as suggested by [16].

$$(x, y) = (-rsin(2\pi p/P), rcos(2\pi p)/P), \quad p = 1, ..., P. \quad (2)$$

The ECLMP texture feature extraction is performed by two operators - $ELMP_c$ and $ELMP_r$ - applied to the luminance image.

The $ECLMP_c$ operator considers the relationship between the local pixel average and the circular neighborhood with



(a) Local Pattern 5×5. (b) Circular Neighborhoods.

Fig. 5. Illustration of a local pattern and the corresponding circular neighborhood.

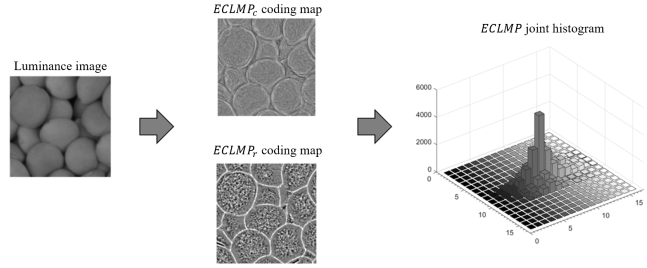


Fig. 6. ECLMP feature vector generation of a luminance image, considering $P = 8$, $r_{out} = 2$, $r_{in} = 1$, $Q = 16$ and $\beta_{c1} = \beta_{r1} = 0.1$.

larger radius r_{out} (Figure 5). This information is captured by the sigmoid function defined in Eq. (3)

$$f(g_{p,r_{out}}) = \frac{1}{1 + \exp\left(\frac{-[g_{p,r_{out}} - m_1]}{\beta_{c1}}\right)}, \tag{3}$$

where β_{c1} is the steepness of the mapping function and m_1 is the average of the gray level values of the pixels in the circular neighborhood, including the central pixel, as presented in Eq. (4)

$$m_1 = \frac{1}{n+1}\left[\left(\sum_{i=1}^{n} g_{p,r_{out}}\right) + g_c\right]. \tag{4}$$

Then, each local pattern is represented by a code generated using Eq. (5), where f is the mapping function defined in Eq. (3). The image codes are stored into a matrix named coding map. Those codes are uniformly quantized in Q elements.

$$ECLMP_c = \text{round}\left(\frac{\left(\sum_{p=1}^{P} f(g_{p,r_{out}})\right) + f(g_c)}{P+1}(Q-1)\right). \tag{5}$$

Inspired by Liu et al. [31], the $ECLMP_r$ operator captures the relationship between the pixels $g_{p,r_{in}}$ located in the circular neighborhood of smaller radius r_{in} and the pixels $g_{p,r_{out}}$ located in the circular neighborhood of larger radius r_{out}. Comparisons are made using the differences between the gray levels of $g_{p,r_{in}}$ and $g_{p,r_{out}}$ as the input of a sigmoid function as defined in Eq. (6), where β_{r1} is the steepness of the curve.

$$z(g_{p,r_{out}}, g_{p,r_{in}}) = \frac{1}{1 + \exp\left(\frac{-[g_{p,r_{out}} - g_{p,r_{in}}]}{\beta_{r1}}\right)}, \tag{6}$$

The differences are then averaged, generating the $ECLMP_r$ codes through Eq. (7), where z is the mapping function defined in Eq. (6). As in the $ECLMP_c$, the codes are uniformly quantized in Q elements and stored in a coding map.

$$ECLMP_r = \text{round}\left(\frac{\sum_{p=1}^{P} z(g_{p,r_{out}}, g_{p,r_{in}})}{P}(Q-1)\right). \tag{7}$$

The ECLMP feature vector is generated by combining the $ECLMP_c$ and $ECLMP_r$ information into a joint histogram [16], which is built using both feature location and value in the coding maps, as shown in Figure 6.

2) Color-Texture Information Extraction: The $ECLMP_c$ and $ECLMP_r$ operators can be easily extended for color textures using the same approach as in the CILMP. Color-texture features are extracted from the RGB channels using the integrative concept: color and texture information are extracted jointly by considering the squared magnitudes of the vectors in the RGB space.

To incorporate the color-texture information, the $ECLMP_c$ operator uses the sigmoid function as defined in Eq. (8), where β_{c2} is the steepness of the curve and m_2 is the average of the squared magnitudes of the pixels in the circular neighborhood including the central pixel (presented in Eq. (9)). The $ECLMP_c$ coding map is generated using Eq. (5), and the codes are uniformly quantized into Q elements.

$$f(g_{p,r_{out}}) = \frac{1}{1 + \exp\left(\frac{-[||g_{p,r_{out}}||^2 - m_2]}{\beta_{c2}}\right)}, \tag{8}$$

$$m_2 = \frac{1}{n+1}\left[\left(\sum_{i=1}^{n} ||g_{p,r_{out}}||^2\right) + ||g_c||^2\right]. \tag{9}$$

The $ECLMP_r$ coding map of the color textures is also obtained using Eq. (5), following the same procedure as for the texture information extraction. However, the color-texture differences between the $g_{p,r_{in}}$ and $g_{p,r_{out}}$ pixels are captured by the sigmoid function defined in Eq. (10), where β_{r2} is the steepness of the curve.

$$z(g_{p,r_{out}}, g_{p,r_{in}}) = \frac{1}{1 + \exp\left(\frac{-[||g_{p,r_{out}}||^2 - ||g_{p,r_{in}}||^2]}{\beta_{r2}}\right)}, \tag{10}$$

Figure 7 shows $ECLMP_c$ and $ECLMP_r$ coding maps of a color texture and the corresponding ECLMP joint histogram. Note that to measure the differences between the pixels located on circular neighborhoods of different radius, the number of samples P should be the same. For example, considering the neighborhood presented in Figure 5, we can set $r_{out} = 2$,

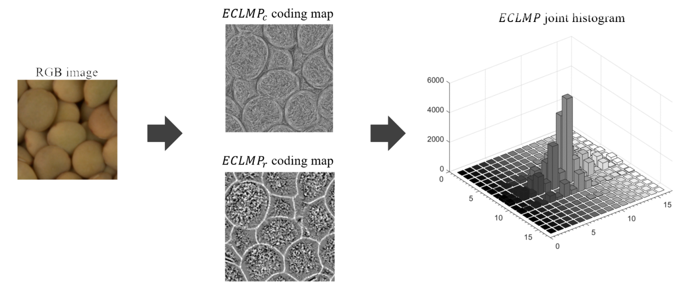


Fig. 7. ECLMP feature vector generation of an RGB image, considering $P = 8$, $r_{out} = 2$, $r_{in} = 1$, $Q = 16$ and $\beta = 0.1$.

$r_{in} = 1$, and $P = 8$ for both radii. To make the notation more understandable, we represent such configuration as $ECLMP(P, r_{out}, r_{in})$ = $ECLMP(8, 2, 1)$.

3) Combining texture and color-texture information: Taking advantage of the multiresolution analysis, we perform the feature extraction using different radii (r_{out}, r_{in}) and number of neighbors (P). Then, the features from different configurations of (P, r_{out}, r_{in}) are concatenated in a parallel approach to get the image feature vector.

To get the image feature vector, the joint histograms are reshaped into 1D features and concatenated. The parameter Q was set to 16, so each joint histogram has $Q \times Q = 16 \times 16 = 256$ bins.

III. Discussions and Conclusions

The Ph.D. thesis proposed three new color texture descriptors: the OCLMP, CILMP and ECLMP. The validation was performed using two publically available image datasets: RawFooT and KTH-TIPS-2b, both containing textures acquired with different illumination sources. The performance of the descriptors was assessed using the accuracy achieved by a K-NN classifier in a classification task. The processing time of each descriptor was also analyzed. The classification accuracy achieved using each feature descriptor was compared to state-of-the-art methods available in the literature.

The first tests were performed using the RawFooT dataset. The ECLMP descriptor achieved 80.9% accuracy, 14 percentage points (pp) above the second best descriptor, the LCC [14]. The ECLMP also achieved better regularity in the description, which was assessed by comparing the minimum accuracy to the average accuracy. The second set of experiments was performed using the KTH-TIPS-2b dataset. In this case, the OCLMP yielded better performance, with accuracy of 87.5%. The CILMP descriptor presented similar performance on both image datasets. The accuracy achieved by this descriptor was 77.8% for the RawFooT dataset, and 76.5% for the KTH-TIPS-2b dataset.

In general, the results indicate that descriptors based on the opponent-color theory are especially efficient at describing textures acquired with changes in the direction of the illumination. The CILMP is the best descriptor for tasks involving multiple light sources. The ECLMP is the best descriptor for tasks involving changes in illumination intensity and temperature.

Publications and Awards

This section is a summary of the work published during this Ph.D. project.

- Negri, T.T.; Gozaga, A. Color Texture Classification under Varying Illumination. In: X Workshop de Viso Computacional, Uberlndia, p. 61-66, 2014.
- Negri, T.T.; Gozaga, A. Color Texture Classification by a local multiscale descriptor. In: XI Workshop de Viso Computacional, São Carlos, p. 292-297, 2015.
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- Negri, T.T.; Zhou, F.; Obradovic, Z.; Gonzaga, A. A Robust Descriptor for Color Texture Classification under Varying Illumination. In: 12th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications (VISIGRAPP), Porto, p. 378-388, 2017.
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- Negri, T.T.; Vieira, R.T.; Gozaga, A. Color Texture Classification by using Opponent Color and Local Mapped Pattern. In: XIII Workshop de Viso Computacional, Natal, 2017.
- Negri, T.T.; Zhou, F.; Obradovic, Z.; Gozaga, A. Extended Color Local Mapped Pattern for Color Texture Classification under Varying Illumination. Journal of Electronic Imaging. v.26, n.1, 2018.
- Vieira, R.T.; Negri, T.T.; Gozaga, A. Improving the Classification of Rotated Images by Adding the Signal and Magnitude Information to a Local Texture Descriptor. Multimidia Tools and Applications, In Print, 2018.
- Visiting Ph.D. Researcher at Temple University, Philadelphia, USA, 2016 - 2017.

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