Color Texture Classification under Varying Illumination

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Abstract—Color texture descriptors have gained a lot of interest in computer vision applications. Methods for grayscale texture analysis have been extended to color images. This paper presents a new descriptor for color texture analysis based on the Local Mapped Pattern (LMP) methodology called Color Local Mapped Pattern (CLMP). For each color channel, C-LMP considers the sum of the differences of each pixel of a given neighborhood to the central pixel as a local pattern that can be mapped to a histogram bin by using a mapping function. The histograms obtained from the color channels are concatenated in a color texture descriptor. The classification performance of the C-LMP is performed over Outex 14 texture database, considering three illumination sources. In our experiments, three different color spaces were considered: RGB, L∗a∗b∗ and HSV. Our results show that the C-LMP has better performance under illumination variances than the best results reported.

Keywords: Color texture, Local Mapped Pattern, LBP, illumination invariance.

I. INTRODUCTION

Texture analysis in digital images plays an important role in many applications such as robotics [1], biometry [2], document processing [3], medicine [4], remote sensing [5] and visual inspection [6]. Methods of texture analysis have usually been applied to gray-scale images. However, new approaches using both color and textures information has been introduced in order to improve the characterization of color textures [7] [8] [9] [10].

The already established methods for grayscale texture analysis as Local Binary Pattern (LBP) and its variations [11] [12], and Gabor filter [13] can be extended to color images. The descriptor is applied to each color channel separately, and the feature vectors obtained from different channels are concatenated into a color texture descriptor [7].

Jain and Healey [14] used the Gabor filter outputs to compute unichrome and opponent features for color texture. Based on the opponent processes in the human visual system, opponent features capture the differences between filtered color channels. In [7], the LBP operator is extended to color texture in a similar manner. Maenpaa and Pietikainen [7] also presented four different methods of combining separate color and texture measures. The color and texture features are combined on similarity measure level or classifier level.

Unichrome and opponent features are also considered in the Color Local Binary Pattern (CLBP) [15]. CLBP combines both color and grayscale features within a feature-level fusion framework for face recognition.

Color histograms were proposed by Swain and Ballard [16] as a feature descriptor. They showed that color histograms are robust to changes in view and to partial occlusion. However, they are not stable over changes in the color of scene illumination [7]. Funt and Finlayson [17] extended Swain’s method to be illumination independent. The color constant color indexing method proposed by them is easy to implement and it works very well at different lighting conditions.

Variation of illumination is one of the challenges in the classification of textures [7]. Natural textures are generally subject to changes in illumination and it is wanted that the texture descriptor is able to cope with these changes.

Maenpaa and Pietikainen [7] compared the performance of several methods to color texture classification on two image databases: Vistex [18] and Outex [19]. In their experiments, five different color spaces were considered: RGB, rg chromaticity coordinates, \( I_1 I_2 I_3 \) [20], \( L^* a^* b^* \) and HSV. In experiments with static illumination all methods presented good performance: the hit-rates reached 95.4%. However, the performance of methods was not so good when there were changes in illumination. The best score was 69.5% and it was achieved by the LBP operator applied in grayscale texture. In their paper, the authors concluded that grayscale texture measures work better than color texture measures under varying illumination.

In a recent work, Ferraz et al. [21] presented a new descriptor called Local Mapped Pattern (LMP). The LMP methodology assumes that each gray-level distribution within an image neighborhood is a local pattern that can be mapped to a histogram bin using a mapping function. In their proposed application the LMP methodology had better performance under varying illumination than the LBP methodology.

In this paper, we propose a novel descriptor for color texture based on the Local Mapped Pattern (LMP) methodology, called Color Local Mapped Pattern (C-LMP). The performance of our proposed color texture descriptor was evaluated over the Outex 14 database [19] and it was compared to the LBP performance and some other methods proposed in [7]. The Outex 14 database provides textures imaged under three different illumination sources, allowing to evaluated if the C-LMP is robust to illumination variances. In our experiments, three different color spaces were considered: RGB, \( L^* a^* b^* \) and HSV.
The remainder of this paper is divided into four sections. In Section II, we briefly describe LBP and LMP methods. Section III give details on the proposed approach C-LMP. The experimental evaluation and the results are presented in Section IV. Finally, we conclude the paper in Section V.

II. LOCAL BINARY PATTERN AND LOCAL MAPPED PATTERN

The LBP provides a way for describing local patterns in a texture as binary codes. The $3 \times 3$ pixels neighborhood shown in Fig. 1(a) is thresholded by the gray-level of the central pixel. The pixel values in the threshold neighborhood, as shown in Fig. 1(b), are multiplied by the respective weights in Fig. 1(c). The result, for this example, is shown in Fig. 1(d). Finally, the values of the eight values are summed to obtain the number of this texture code. For this example:

$$LBP_{\text{code}} = 1 + 0 + 0 + 8 + 0 + 32 + 0 + 128 = 169$$

![Fig. 1: The Local Binary Pattern [11] a) Image gray-level b) Thresholded neighborhood c) Weighting matrix d) Generated pattern.](image)

Ojala et al. [12] proposed the local binary pattern (LBP) operator where the eight gray-level differences within a pixel neighborhood are operated by Eq. (1) and the result is recorded in an 8-bit number.

$$LBP = \sum_{i=1}^{8} S(g_i - g_{ci})2^{i-1}, S(x) = \begin{cases} 1, & \text{if } g_i \geq g_{ci} \\ 0, & \text{if } g_i < g_{ci} \end{cases}$$

The center pixel neighborhood is defined as:

<table>
<thead>
<tr>
<th>$g_1$</th>
<th>$g_2$</th>
<th>$g_3$</th>
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<tbody>
<tr>
<td>$g_4$</td>
<td>$g_5$</td>
<td>$g_6$</td>
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<tr>
<td>$g_7$</td>
<td>$g_8$</td>
<td>$g_9$</td>
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</table>

That is, the LBP approach maps a pixel gray-level structure, within a neighborhood, to a histogram of 256 bins. This formulation is limited to a $3 \times 3$ pixels’ neighborhood. Intending to expand the LBP method to operate in a general $W \times W$ neighborhood and mapping the resulting code to a histogram of B bins, Ferraz et al. [21] proposed to equate the LBP as in Eq. (2) where the function $f_g$ is the Heaviside function shown in Eq. (3), $B$ is the number of histogram bins and $P(i)$ is the weighting matrix shown in Fig. 1(c).

$$LBP = \text{round} \left( \frac{\sum_{i=1}^{W} f_g P(i)}{\sum_{i=1}^{W} P(i)} \right) (B - 1)$$

$$f_g = H[g_i - g_0] = \begin{cases} 1, & \text{if } g_i - g_0 \geq 0 \\ 0, & \text{if } g_i - g_0 < 0 \end{cases}$$

By using the equation (3), the Heaviside function became the “mapping function”, of a pixel gray-level structure in a neighborhood, to a specific code in the histogram and the method was called Local Mapped Pattern (LMP).

The basic LBP is not well suited for rotated textures due its weighting matrix based on the power of two [22]. New researches were published by the same authors, aimed to solve this problem [12] with the introduction of the $LBP_{\beta,R}^{P,R}$ (rotation invariant uniform). In this new version, the gray levels in the pixel neighborhood are sampled in a circular chain. Samples that are not located in the pixels center are interpolated. It is necessary to set the number of samples ($P$) and the neighborhood radius ($R$).

The LMP operator considers the sum of the differences of each gray-level of a given neighborhood to the central pixel as a local pattern that can be mapped to a histogram bin by using a mapping function. In the LMP methodology, Heaviside step function used in Eq. (2) can be replaced with any function. Furthermore, the weighting matrix can be chose according to the application and the $B$ parameter can be optimized.

For texture analysis, the authors suggest to use a smooth approximation to the Heaviside step function by a logistic curve, or a common sigmoid curve as in Eq. (4)

$$f_g = \frac{1}{1 + e^{-\beta(x-a)}}$$

where $\beta$ is the curve slope. So that the descriptor is robust to changes of rotation, the proposed weighting matrix is:

$$P(i) = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$$

Thus, each pattern defined by a $W \times W$ neighborhood will be mapped to a histogram bin $h_B$ using Eq. (6). Fig. 2 shows a comparison between the LBP and LMP code generated for the same neighborhood of one texture sample, considering $B = 256$.

$$h_B = \text{round} \left( \frac{\sum_{i=1}^{W} P(i)}{\sum_{i=1}^{W} P(i)} \right) (B - 1)$$

Sigmoid function, whose graph is “S-shaped” curve, appears in a great variety of contexts, such as the transfer functions of many neural networks. Their ubiquity is no accident: these curves are among the simplest nonlinear curves, striking a graceful balance between linear and nonlinear behavior.
III. COLOR LOCAL MAPPED PATTERN

Based on the color texture descriptor proposed by Maenppa and Pietikainen [7], we investigated the use of the LMP descriptor in color textures. In this paper, we propose the Color Local Mapped Pattern (C-LMP) by applying the LMP method to each color channel.

As well as in the LMP, the sum of the differences of each pixel value of a given neighborhood to the central pixel is considered as a local pattern that can be mapped to a histogram bin by using a mapping function. The histograms obtained from the different color channels are concatenated, generating the color texture descriptor C-LMP. Fig. 3 shows an example of the C-LMP methodology applied in a RGB image.

IV. EXPERIMENTAL EVALUATION

A. Experimental setup

To evaluate the performance of the C-LMP, we have performed an experiment on the Outex database, which is a public framework provided by the University of Oulu, Finland, composed of a bank of textures and test suites. In our experiment, the test suit Outex_TC_00014 (Outex 14) [7] was used. Outex 14 texture database contains 68 textures of size 746 × 538 pixels, each one imaged under three different illumination sources. The reference illumination source was a 2856 K incandescent CIE A light. The other illumination sources are 2300 K horizon sunlight and 4000 K fluorescent TL84. All images were imaged with a 100 dpi resolution and 0° rotation. Fig. 4 shows an example of the each texture in the reference illumination. Fig. 5 shows the same texture imaged under three different illumination sources.

The 68 Outex textures in the reference illumination were used as training data. The textures were split into sub-images of 128 × 128 pixels. Since the size of the original images was 746 × 538 pixels, 20 sub-images were obtained of each texture, producing 1360 samples. Half of the samples from each texture were used in training, that is, 680 samples. To perform the division of the sub-images, a checkerboard pattern was used to split the set in two. Thus, there were 1360 samples in the test data.

B. Texture Classification

For each texture sample, and considering each pixel in a neighborhood of 3x3 pixels, the C-LMP histogram bins were mapped by using the sigmoid function (Eq. 4) and the unit weighting matrix (Eq. 5). The optimal value of \( \beta \) (curve slope) was tuned by using a training set. The comparison between two samples is performed by employing a distance metric to evaluate the best fit between the two histograms. A query or “model” sample is considered to be correctly classified if it has the shortest distance from the same class of the training sample as illustrated in Figure 6.
Fig. 3: The C-LMP methodology applied on RGB color space.

Fig. 4: Outex textures ([7]).
Fig. 5: The same texture imaged under three different illumination sources.

The method performance was evaluated using the chi-square ($\chi^2$) distance metric given by

$$\chi^2(S, M) = 2 \sum_{b=1}^{B} \frac{(S_b - M_b)^2}{S_b + M_b},$$

where $S$ is the image sample, $M$ is the query image (or model image), $B$ is the number of bins of the compared histograms, $S_b$ is the number of sample values in each bin $b$, and $M_b$ is the number of model probabilities in each bin $b$.

Then, the confusion matrices are generated with true positives ($TP$), or the number of correctly classified samples, and false negatives ($FN$), or the wrongly classified samples, for all of the query samples. The hit-rate ($H$) or sensitivity can be calculated by

$$H = \frac{TP}{TP + FN}.$$

As C-LMP is a parametric model, we need to adjust the sigmoid curve slope (\(\beta\)) and the number of the histogram bins (\(B\)). The best values for the \(\beta\) parameter are reached as soon as the sensitivity (\(H\)) is maximum using all the texture samples from the training set, with leave-one-out cross validation. In this work, we chose \(B = 256\) without any optimization. The \(\beta\) parameter was adjusted for each color channel separately on the three color spaces investigated: RGB, \(L^*a^*b^*\) and HSV. The best values to the \(\beta\) curve slope are presented in Table I.

The database used in our study as well as the methodology of classification is the same used by Maenppa and Pietikainen [7] in order to allow the comparison of the performance of descriptors. In [7], several experiments were performed. Color histograms [16] and the color constant color indexing method [17] were tested in various color spaces and the opponent color texture method [14] was applied using LBP operator and Gabor filters. LBP operator and Gabor filters [11] [12] [13] were also applied in color texture and gray-scale texture. In addition, methods combining separate color and texture features were tested. The best score was 69.5\% and it was reached by a variation of LBP operator applied in gray-scale texture.

Among all the methods proposed by Maenppa and Pietikainen applied to color texture analysis (color histograms, color constant color indexing, LBP operator and Gabor filters applied to color texture analysis, opponent color texture and methods combining separate color and texture features) in different color spaces (RGB, rg chromaticity coordinates, \(I_1I_2I_3\) [20], \(L^*a^*b^*\) and HSV) the best results were obtained by the \(LBP(8, 1; 16, 2, 24, 5)\) in the \(L^*a^*b^*\) space (67.8\% of sensitivity). Table II shows these results compared to the C-LMP performance.

### Table I: Best values to \(\beta\) curve slope

<table>
<thead>
<tr>
<th>Color Spaces</th>
<th>Channels</th>
<th>(\beta)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RGB</td>
<td>R</td>
<td>0.0990</td>
</tr>
<tr>
<td></td>
<td>G</td>
<td>0.3500</td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>0.3890</td>
</tr>
<tr>
<td>(L^*a^<em>b^</em>)</td>
<td>(L^*)</td>
<td>0.0600</td>
</tr>
<tr>
<td></td>
<td>(a^*)</td>
<td>0.0149</td>
</tr>
<tr>
<td></td>
<td>(b^*)</td>
<td>0.0359</td>
</tr>
<tr>
<td>HSV</td>
<td>H</td>
<td>0.0005</td>
</tr>
<tr>
<td></td>
<td>S</td>
<td>1.0014</td>
</tr>
<tr>
<td></td>
<td>V</td>
<td>0.3700</td>
</tr>
</tbody>
</table>
The C-LMP applied in any of the three color spaces investigated overcame all methods presented in [7]. The best result was achieved in the $L^*a^*b^*$ color space (83.16%), increasing 19.65% the hit-rate compared to $LBP(8,1+u_{10.3}+u_{24.5})$ applied in the gray-scale texture.

The evidence that grayscale images are better for texture analysis than color textures in varying illumination presented in [7] is clearly not true. The results presented in this paper show that the C-LMP descriptor works well with color texture, in addition to being robust to illumination variances.

For future works, other experiments can be performed to investigate the use of other color spaces and test the recent variations of LMP descriptor presented in [21].

### V. CONCLUSION

In this paper, we proposed a novel method for color texture classification based on the Local Mapped Pattern (LMP) methodology. The proposed descriptor was evaluated in textures images under different illumination sources. The results were compared to the performance of other methodologies over the same image database. C-LMP approach presented better results than all methods compared, showing that the proposed methodology is robust to changes in illumination and it works well for color texture classification.

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