Haralick feature extraction from LBP images for color texture classification

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Abstract— **In this paper, we present a new approach for color texture classification by use of Haralick features extracted from co-occurrence matrices computed from Local Binary Pattern (LBP) images. These LBP images, which are different from the color LBP initially proposed by Mäenpää and Pietikäinen, are extracted from color texture images, which are coded in 28 different color spaces.**
An iterative procedure then selects among the extracted features, those which discriminate the textures, in order to build a low dimensional feature space.
Experimental results, achieved with the BarkTex database, show the interest of this method with which a satisfying rate of well-classified images (85.6%) is obtained, with a 10-dimensional feature space.

Keywords— **Color texture classification, Feature extraction, LBP images.**

I. INTRODUCTION

Color texture classification is a major field of development for various vision applications, and particularly for the industrial quality control where color textures have to be characterized in order to detect defects on color texture areas and sort the products into different categories [1].

Many authors have shown that the use of color improves the characterization of color textures and consequently the results of texture classification [2], [3], [4], [5]. That is why many relevant texture descriptors, initially defined for grey images, have been extended to color and used to classify color textures, like Markov random fields [6], wavelet transform [7], [8], [9], co-occurrence matrices [3] or Local Binary Patterns (LBP). LBP, which have initially been proposed in 1996 by Ojala to describe the textures present in grey level images [10], have then been extended to color by Mäenpää and Pietikäinen [2], [11].

The use of the LBP images in order to characterize color textures is very expensive, since it requires 9 LBP images deduced from the original color image. Indeed, LBP images are based on a scalar analysis of colors. In this paper, we propose a new color LBP image, based on a vectorial analysis of colors. This new approach provides only one single color LBP image which characterizes the color texture.

In order to classify color textures, we propose to follow a classical approach, defined in section III : we compute the co-occurrence matrix of this new color LBP image and extract well-known Haralick features from this matrix.

Futhermore, the analysis of the color properties is not restricted to the acquisition color space (R, G, B) (see section II) and there exists a lot of color spaces which respect different properties [12]. None of them is adapted to the classification of all kinds of color textures [13]. That is why we propose to select the texture features from color texture images coded in different color spaces (see section IV) [14].

The selection of the Haralick features computed in different color spaces significantly improves the classification quality and also allows to work with a low-dimensional feature space [13]. This is important within the framework of industrial quality control to decrease the processing time. This discriminating low-dimensional feature space is built by using the iterative selection procedure described in the section IV-B.

Experimental results, achieved with the BarkTex benchmark database, show the interest of this approach in the last section [15].

II. COLOR REPRESENTATION

A. Color space and texture analysis

Color analysis is not restricted to the (R, G, B) color space and there exists a large number of color spaces which respect different properties [12]. These color spaces can be classified into four families : the primary color spaces, the luminance-chrominance color spaces, the perceptual color spaces and the independent color component spaces (see Fig. 1). Figure 1 shows that these families can be divided in subfamilies too.

Furthermore, Palm, Drimbarean and Chindaro have compared the performances of color texture classification reached by using color texture features extracted from images whose pixel color is represented in different color spaces [3], [4],
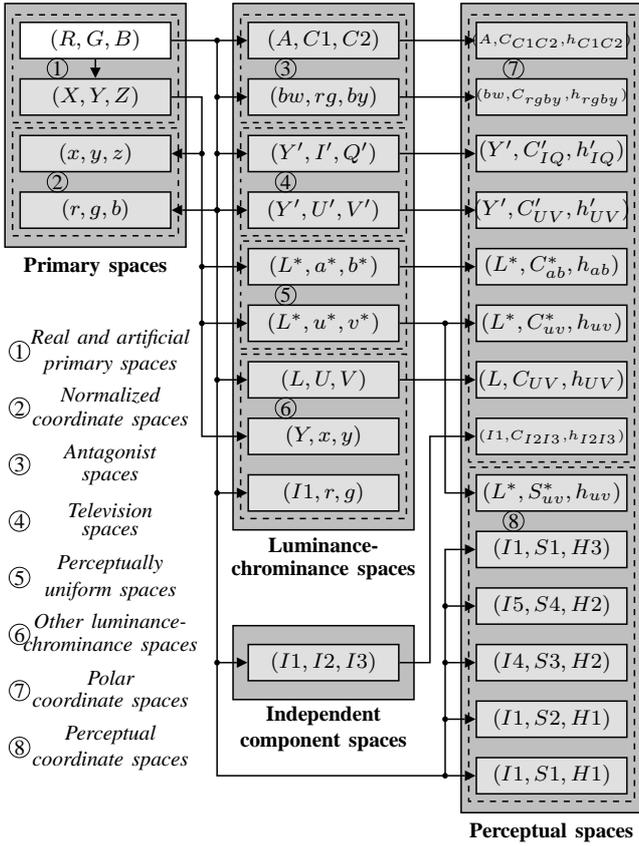
Fig. 1. Color space families.

[5]. The synthesis of these works does not allow to conclude on the definition of a single color space adapted to color texture analysis. In order to take into account the properties of different color spaces, Chindaro proposes to merge different classifiers where the images are coded in different color spaces [5]. Likewise, Vandenbroucke proposes to select local statistical features, which are computed from different color components [16]. In this paper, we propose also to associate several color spaces in order to characterize the textures by extracting the color texture features from color images coded in each of the $N_S = 28$ color spaces of Fig. 1.

B. Color order relation

In our approach, the color ranks of pixels are compared to compute the LBP images (see section III-A.2). The color of pixels is represented by a vector, but as there does not exist a total order between vectors, we need to consider a partial order relation [18]. We choose to use for its simplicity, the partial order relation used by vector median filters and defined as follows :
For each color space $S = (C_1, C_2, C_3)$ of Fig. 1, the color $a = [C_1^a \ C_2^a \ C_3^a]$ precedes the color $b = [C_1^b \ C_2^b \ C_3^b]$, with respect to the origin point $(0, 0, 0)$, if

$$\sqrt{(C_1^a)^2 + (C_2^a)^2 + (C_3^a)^2} \leq \sqrt{(C_1^b)^2 + (C_2^b)^2 + (C_3^b)^2}.$$

This rule is based on the comparison of the norms of the two color vectors.

After having presented the $N_S = 28$ color spaces used to characterize more effectively the textures, and the order relation required to compare two colors, we explain in the next section the computation of the color texture features.

III. COLOR TEXTURE FEATURES

In this section, we firstly explain how the LBP images are computed from the original color texture images. Then, we detail the computation of the co-occurrence matrices which are extracted from these LBP images, and finally we present Haralick features which are used to reduce the large amount of information of the co-occurrence matrices, while preserving their relevance.

A. Local binary pattern images

1) Scalar LBP images: Local Binary Patterns (LBP) have initially been proposed in 1996 by Ojala to describe the textures present in grey level images [10]. These texture descriptors are very interesting because they are particularly well-adapted to real-time quality control applications as they are both fast and easy to implement [19]. They have then been extended to color by Mäenpää and Pietikäinen and used in several color texture classification problems [2], [11].

These color texture descriptors are defined as follows :
Let C_k and $C_{k'}$, be two of the three color components of the color space $S = (C_1, C_2, C_3)$ $(k, k' \in \{1, 2, 3\})$ and $LBP_\mathcal{N}^{C_k, C_{k'}}[P]$, be the LBP which represents the local pattern in the neighborhood $\mathcal{N}$ of the pixel P, for the components C_k and $C_{k'}$:

- first, the color component $C_{k'}$ of each pixel P' of the neighborhood $\mathcal{N}$ is thresholded into two levels (0 and 1) by using the color component $C_k(P)$ of the considered pixel P as threshold T :
  if $C_{k'}(P') \geq C_k(P)$,
  then $C_{k'}(P') = 1$,
  else $C_{k'}(P') = 0$.
- the result of each thresholding is then coded thanks to a weight mask :

1	2	4
8		16
32	64	128

- the weighted values are finally summed in order to obtain the value of the LBP $LBP_\mathcal{N}^{C_k, C_{k'}}[P]$.

Figure 2 illustrates the computation steps achieved to obtain the LBP images $LBP_{8-N}^{C_1, C_1}[\mathbf{I}]$, $LBP_{8-N}^{C_1, C_2}[\mathbf{I}]$ and $LBP_{8-N}^{C_2, C_1}[\mathbf{I}]$ extracted from the original image $\mathbf{I}$, whose the pixel color is represented by the cell $\boxed{\begin{smallmatrix} C_1 \\ C_2 \\ C_3 \end{smallmatrix}}$, and where the neighborhood $\mathcal{N}$ here considered to compute these LBP images is the 8-neighborhood, denoted $8 - N$ (see Fig. 4).

For example, for the computation of $LBP_{8-N}^{C_1, C_2}[P_1]$, P_1 being represented by the cell $\boxed{\begin{smallmatrix} 200 \\ 0 \\ 0 \end{smallmatrix}}$ in Fig. 2, the color component C_2 of each of the 8 neighboring pixels is compared with the color component $C_1(P_1) = 200 = T$.
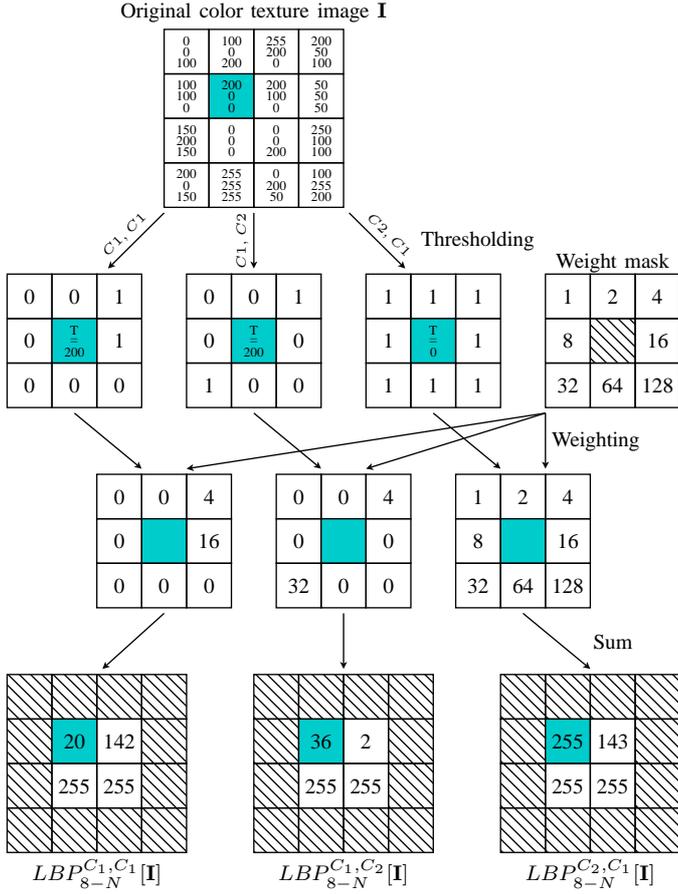For the neighboring pixel located down left, for example, the

Original color texture image **I**

0 0 100	100 0 200	255 200 0	200 50 100
100 100 0	200 0 0	200 100 0	50 50 50
150 200 150	0 0 0	0 200 0	250 100 100
200 0 150	255 255 255	0 200 50	100 255 200

C_1, C_1 C_1, C_2 C_2, C_1 Thresholding   Weight mask

Thresholding:

0	0	1
0	T=200	1
0	0	0

0	0	1
0	T=200	0
1	0	0

1	1	1
1	T=0	1
1	1	1

Weight mask:

1	2	4
8		16
32	64	128

Weighting:

0	0	4
0		16
0	0	0

0	0	4
0		0
32	0	0

1	2	4
8		16
32	64	128

Sum:

20	142
255	255

36	2
255	255

255	143
255	255

$LBP_{8-N}^{C_1,C_1}[\mathbf{I}]$ $LBP_{8-N}^{C_1,C_2}[\mathbf{I}]$ $LBP_{8-N}^{C_2,C_1}[\mathbf{I}]$

Fig. 2. The different steps to obtain the LBP images $LBP_{8-N}^{C_1,C_1}[\mathbf{I}]$, $LBP_{8-N}^{C_1,C_2}[\mathbf{I}]$ and $LBP_{8-N}^{C_2,C_1}[\mathbf{I}]$ extracted from the original image **I**.

Original color texture image **I**

0 0 100	100 0 200	255 200 0	200 50 100
100 100 0	200 0 0	200 100 0	50 50 50
150 200 150	0 0 0	0 200 0	250 100 100
200 0 150	255 255 255	0 200 50	100 255 200

Thresholding

0	1	1
0	T=200	1
1	0	1

Weight mask

1	2	4
8		16
32	64	128

Weighting

0	2	4
0		16
32	0	128

Sum

182	135
255	243

LBP image $LBP_{8-N}^{C_1,C_2,C_3}[\mathbf{I}]$

Fig. 3. The different steps done to obtain the color LBP image $LBP_{8-N}^{C_1,C_2,C_3}[\mathbf{I}]$ extracted from the original image **I**.

result of the thresholding is 1 ($200 \geq T$). This result is then weighted by 32.

After having weighted the 8 thresholding values, we sum them and obtain $LBP_{8-N}^{C_1,C_2}[P_1] = 0+0+4+0+0+32+0+0 = 36$.

For a given neighborhood $\mathcal{N}$, a color image **I** coded in the (C_1, C_2, C_3) color space is characterized by the 9 following color LBP images : $LBP_{\mathcal{N}}^{C_1,C_1}[\mathbf{I}]$, $LBP_{\mathcal{N}}^{C_2,C_2}[\mathbf{I}]$, $LBP_{\mathcal{N}}^{C_3,C_3}[\mathbf{I}]$, $LBP_{\mathcal{N}}^{C_1,C_2}\mathbf{I}]$, $LBP_{\mathcal{N}}^{C_2,C_1}[\mathbf{I}]$, $LBP_{\mathcal{N}}^{C_1,C_3}[\mathbf{I}]$, $LBP_{\mathcal{N}}^{C_3,C_1}[\mathbf{I}]$, $LBP_{\mathcal{N}}^{C_2,C_3}[\mathbf{I}]$ et $LBP_{\mathcal{N}}^{C_3,C_2}[\mathbf{I}]$.

Pietikäinen and Mäenpää propose to compute the histogram from each of these 9 LBP images, and to concatenate these histograms into a single one to characterize the color textures. They then use a log-likelihood dissimilarity measure to classify the color texture images with this LBP distribution [2], [11].

2) Vectorial LBP images: Our approach differs from this initial definition. Indeed, instead of comparing the color components of pixels, we compare their color rank thanks to the order relation defined in the section II-B.
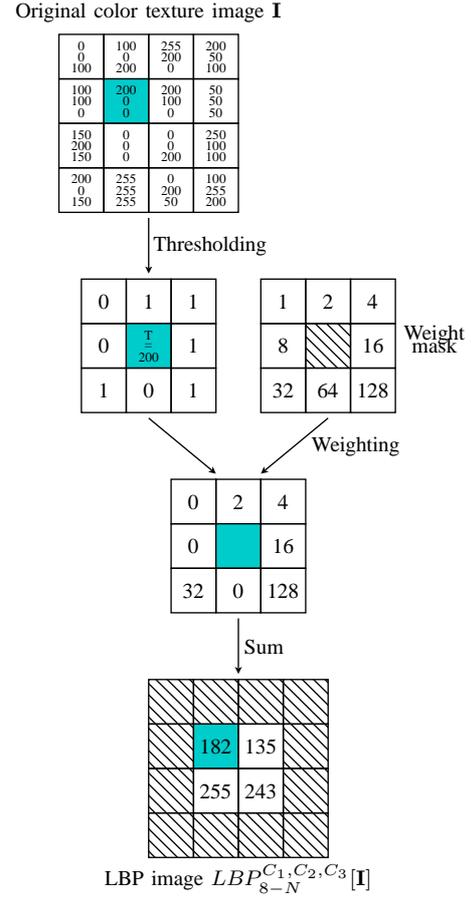
This color texture descriptor is defined as follows :
Let $LBP_{\mathcal{N}}^{S}[P]$, be the LBP image which represents the local pattern in the neighborhood $\mathcal{N}$ of the pixel P coded in the color space S :

- For each pixel P, we firstly compare the color $C(P) = [C_1(P) \ C_2(P) \ C_3(P)]$ of this pixel with the color $C(P') = [C_1(P') \ C_2(P') \ C_3(P')]$ of each neighboring pixel P', thanks to the color order relation :
  if $\sqrt{(C_1(P'))^2 + (C_2(P'))^2 + (C_3(P'))^2} \leq$
  $$\sqrt{(C_1(P))^2 + (C_2(P))^2 + (C_3(P))^2},$$
  then $C(P') = 1$,
  else $C(P') = 0$.
- the result of each thresholding is then coded thanks to the weight mask proposed by Mäenpää and Pietikäinen [2], [11],
- the weighted values are finally summed in order to obtain the value of the color LBP $LBP_{\mathcal{N}}^{S}[P]$.

Figure 3 illustrates the computation steps done to obtain the color LBP image $LBP_{8-N}^{(C_1,C_2,C_3)}[\mathbf{I}]$ from the original image **I** whose the pixel color is represented by the cell $\boxed{\begin{smallmatrix} C_1 \\ C_2 \\ C_3 \end{smallmatrix}}$.

For example, for the pixel P_1, P_1 being represented by the cell $\begin{array}{c} 200 \\ 0 \\ 0 \end{array}$ in Fig. 3, the color of each of its 8 neighbors is compared with the threshold $T = \sqrt{(200)^2 + (0)^2 + (0)^2}$ thanks to the following relations :

1) $\sqrt{(0)^2 + (0)^2 + (100)^2} < T$
2) $\sqrt{(100)^2 + (0)^2 + (200)^2} \geq T$
3) $\sqrt{(255)^2 + (200)^2 + (0)^2} \geq T$
4) $\sqrt{(200)^2 + (100)^2 + (0)^2} \geq T$
5) $\sqrt{(0)^2 + (0)^2 + (200)^2} \geq T$
6) $\sqrt{(0)^2 + (0)^2 + (0)^2} < T$
7) $\sqrt{(150)^2 + (200)^2 + (150)^2} \geq T$
8) $\sqrt{(100)^2 + (100)^2 + (0)^2} < T$

The pixels whose color precedes the pixel P_1 ones are labeled "0". Otherwise they are labeled "1" (see Fig. 3).
The result of each thresholding is then coded thanks to the weight mask and the weighted values are finally summed to obtain the value of $LBP_{\text{8-neighborhood}}^{(C_1,C_2,C_3)}[P_1]$:
$LBP_{8-N}^{(C_1,C_2,C_3)}[P_1] = 0 + 2 + 4 + 0 + 16 + 32 + 128 = 182$.

The strong point of our approach is that it allows to characterize color textures only with one color LBP image, contrary to Mäenpää and Pietikäinen's definition where 9 LBP images are extracted from the original image to characterize the color textures.

Otherwise this definition of color LBP images allows to emphasize the local color variations, as we will see in the section V-B. Therefore it is interesting to extract from these LBP images, texture features which measure the grey scale distribution and consider the spatial interactions between pixels, instead of extracting histograms, as Mäenpää and Pietikäinen do. We thus choose to use Haralick features computed from co-occurrence matrices to test the effectiveness of the LBP images for color texture classification.

B. Haralick features extracted from co-occurrence matrices

Co-occurrence matrices, introduced by Haralick [20], are statistical descriptors which both measure the grey scale distribution in an image and consider the spatial interactions between pixels.
These texture descriptors are defined as follows :
Let $M_{\mathcal{N}'}[\mathbf{I}]$, the co-occurrence matrix which measures the spatial interactions between the pixels of the image $\mathbf{I}$. The cell $M_{\mathcal{N}'}[\mathbf{I}](i,j)$ of this matrix contains the number of times that a pixel P whose grey level $G(P)$ is equal to i, is the neighbor of a pixel Q whose grey level $G(Q)$ is equal to j, according to the neighborhood $\mathcal{N}'$.

As they measure the local interaction between pixels, the co-occurrence matrices are sensitive to significant differences of spatial resolution and image size. To decrease this sensitivity, it is necessary to normalize these matrices by the total co-

occurrence number $\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} M_{\mathcal{N}'}[\mathbf{I}](i,j)$, where N is the quantization level number. The normalized color co-occurrence matrix $m_{\mathcal{N}'}[\mathbf{I}]$ is defined by :

$$m_{\mathcal{N}'}[\mathbf{I}] = \frac{M_{\mathcal{N}'}[\mathbf{I}]}{\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} M_{\mathcal{N}'}[\mathbf{I}](i,j)}.$$

Different neighborhoods $\mathcal{N}'$ can be considered to compute the co-occurrence matrices. The first element to be considered is the shape of the neighborhood. Figure 4 shows different 3x3 neighborhood shapes.
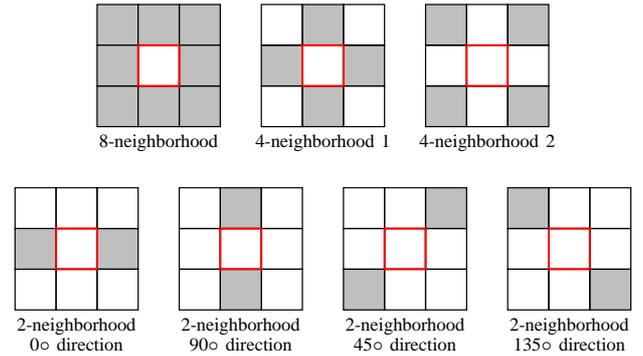

Fig. 4. Example of different 3x3 neighborhood shapes in which neighboring pixels are labeled as gray.

The choice of the neighborhood shape depending on the analysed textures [21], we will see in section V-B that the 8-neighborhood is the best-adapted for our application since it takes into account all directions.

The second element of the neighborhood to be considered is the distance d between the considered pixel P and its neighbors. Figure 5 illustrates the 8-neighborhood, for a given distance d.
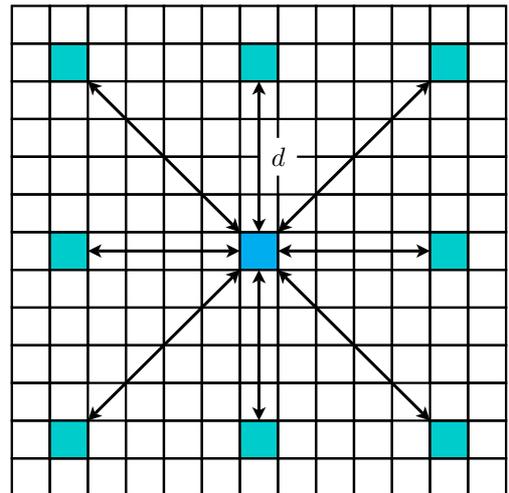

Fig. 5. Illustration of the neighborhood used to compute the co-occurrence matrices, for a given distance d (in number of pixels).

Palm uses different spatial city-block distances d to compute co-occurrence matrices for the classification of the BarkTex database images : $d = 1, 5, 10, 15, 20$ [3], [15]. He obtains the best classification results for the distances $d = 1$ and $d = 5$. That is why we choose to consider $N_D = 5$ different distances ($d = 1, 2, 3, 4, 5$) to characterize the color texture images of the BarkTex database.

The co-occurrence matrices characterize the textures, but they cannot be easily exploited for color texture classification because they contain a large amount of information. To reduce it, while preserving the relevance of these descriptors, Haralick proposes to use $N_H = 14$ features, denoted f_H^1 to f_H^{14}, extracted from each matrix [20].

IV. FEATURE SELECTION

A. Candidate color texture features

For each image $\mathbf{I}$ coded in a color space S, we compute one single color LBP image $LBP_{8-N}^S[\mathbf{I}]$. Then, for each of the $N_D = 5$ neighborhoods $\mathcal{N}$ corresponding to the five different distances, we extract one co-occurrence matrix from this LBP image ($m_{\mathcal{N}'}\left[LBP_{8-N}^S[\mathbf{I}]\right]$). Finally 14 Haralick features are extracted from each matrix. The number of color spaces used here being equal to $N_S = 28$, we examine $N_f = N_H \times N_D \times N_S = 14 \times 5 \times 28 = 1960$ color texture features denoted x^f, $f = 1, \ldots, N_f$. Figure 6 shows how these candidate color texture features are extracted.
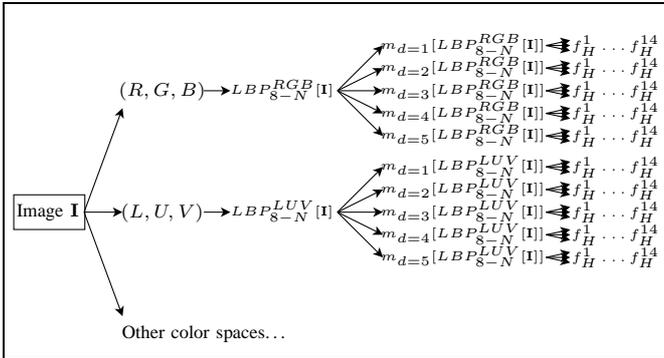

Fig. 6. Candidate color texture features.

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Since the total number N_f of color texture features is very high, it is interesting to select the most discriminating ones in order to reduce the size of the feature space and decrease the classification time.

B. Iterative selection

The determination of the most discriminating feature space is achieved thanks to an iterative selection procedure based on a supervised learning scheme. This non-exhaustive procedure has given very good results to select an hybrid color space for color image segmentation [14], [17].

In a first time, N_ω learning images which are representative of each of the N_T texture classes are interactively selected by the user. Then, the procedure selects automatically the features which discriminate the N_T texture classes among the $N_f = 1960$ color texture features, thanks to the following iterative selection procedure.

At each step s of this procedure, an informational criterion J_s is calculated in order to measure the discriminating power of each candidate feature space. At the beginning of this procedure ($s = 1$), the N_f one-dimensional candidate feature spaces, defined by each of the N_f available color texture features, are considered. The candidate feature which maximizes J_1 is the best one for discriminating the texture classes. It is selected at the first step and is associated in the second step of the procedure ($s = 2$) to each of the $(N_f - 1)$ remaining candidate color texture features in order to constitute $(N_f - 1)$ two-dimensional candidate feature spaces. We consider that the two-dimensional space which maximizes J_2 is the best space for discriminating the texture classes...

In order to only select color texture features which are not correlated, we measure, at each step $s \geq 2$ of the procedure, the correlation between each of the available color texture features and each of the $s - 1$ other color texture features constituting the selected $s-1$ dimensional space. The considered features will be selected as candidate ones only if their correlation level with the color texture features already selected is lower than a threshold fixed by the user [14].

We assume that the more the clusters associated to the different texture classes are well separated and compact in the candidate feature space, the higher the discriminating power of the selected color texture features is. That leads us to choose measures of class separability and class compactness as measures of the discriminating power.

At each step s of the procedure and for each of the $(N_f - s + 1)$ s-dimensional candidate feature spaces, we define, for the ith learning image $\omega_{i,j}$ ($i = 1, \ldots, N_\omega$) associated to the texture class T_j ($j = 1, \ldots, N_T$), a color texture feature vector $X_{i,j} = [x_{i,j}^1, ..., x_{i,j}^s]^{\mathrm{T}}$ where $x_{i,j}^s$ is the sth color texture feature.

The measure of compactness of each texture class T_j is defined by the within-class dispersion matrix Σ_C:

$$\Sigma_C = \frac{1}{N_\omega \times N_T} \times \sum_{j=1}^{N_T} \sum_{i=1}^{N_\omega} (X_{i,j} - M_j)(X_{i,j} - M_j)^{\mathrm{T}}$$

where $M_j = [m_j^1, ..., m_j^s]^{\mathrm{T}}$ is the mean vector of the s color texture features of the class T_j and N_ω the number of images by class.

The measure of the class separability is defined by the between-class dispersion matrix Σ_S:

$$\Sigma_S = \frac{1}{N_T} \times \sum_{j=1}^{N_T} (M_j - M)(M_j - M)^{\mathrm{T}}$$

where $M = [m^1, ..., m^s]^T$ is the mean vector of the s color texture features for all the classes.

The most discriminating feature space maximizes the information criterion :

$$J_s = \mathrm{trace}\Big((\Sigma_C + \Sigma_S)^{-1}\Sigma_S\Big)$$

V. EXPERIMENTAL RESULTS

In order to show the interest of our method for color texture classification, experimental results are achieved with the color textures of the BarkTex database [15]. After having described this benchmark database and shown some examples of LBP images extracted from BarkTex textures, the results of selection and classification will be presented and analyzed.

A. BarkTex database

Color images of the BarkTex database are equally divided into six tree bark classes (**Betula pendula** (T_1), **Fagus silvatica** (T_2), **Picéa abies** (T_3), **Pinus silvestris** (T_4), **Quercus robus** (T_5), **Robinia pseudacacia** (T_6)). Each class regroups 68 images of size 128×192 yielding a collection of 408 images.

To build the learning set, we have extracted $N_\omega = 32$ learning images $\omega_{i,j}$ of each texture class T_j.

For the classification, 36 test images for each texture class T_j are used. Figure 7 illustrates a subset of learning images on the left and a part of the images used to test our classification method on the right.

These test images are classified thanks to the k-nearest neighbor classifier. We choose to use the 10-dimensional most discriminating feature space selected by the selection procedure and a number of neighbors k equal to 7 to classify the test images, because these parameters give the best rate of well-classified images.

B. Examples of LBP images

Figure 8 illustrates six color texture images (coded in the (R, G, B) color space) and their associated LBP images. We can notice that these LBP images emphasize not only the pattern of each image, but also the local color variations.

Otherwise, contrary to the original images where the textures mainly contain vertical patterns, the patterns present in the associated LBP images have no privileged direction. So, as the choice of the neighborhood used to compute co-occurrence matrices depends on the analyzed textures [21], and as these matrices are extracted from the LBP images and not directly from original image, we choose the 8-neighborhood to compute the co-occurrence matrices in order to take into account all directions.

C. Selected texture feature space

The supervised learning procedure iteratively selects discriminating color texture features. Table 1 shows that, at the first iteration step ($s = 1$), the most discriminating color texture feature which maximises J_1, is the tenth Haralick feature f_H^{10} extracted from the co-occurrence matrix $m_{d=3}[LBP_{8-N}^{(X,Y,Z)}]$. This matrix measures the spatial interactions between the pixels of the LBP image $LBP_{8-N}^{(X,Y,Z)}$ in a 8-neighborhood where the distance d between the analysed pixel and its neighbors is equal to $d = 3$. $LBP_{8-N}^{(X,Y,Z)}$ is extracted from the BarkTex images coded in the (X, Y, Z) color space and the neighborhood taken into account to compute this LBP image is also a 8-neighborhood. The discriminating power of this color texture feature is equal to 0.7518.

At the second iteration step, this feature is associated to the Haralick feature f_H^{10} extracted from the color co-occurrence matrix $m_{d=2}[LBP_{8-N}^{(Y',U',V')}]$ to constitute the most discriminating two-dimensional feature space with respect to J_2 : the discriminating power of this feature space is equal to 1.3495.

Table 1. Color texture features iteratively selected.

s	Co-occurrence matrix extracted from the LBP image	Haralick feature	J_s
1	$m_{d=3}[LBP_{8-N}^{(X,Y,Z)}]$	f_H^{10}	0.751792
2	$m_{d=2}[LBP_{8-N}^{(Y',U',V')}]$	f_H^{10}	1.34946
3	$m_{d=4}[LBP_{8-N}^{(L^*,S_{uv}^*,h_{uv})}]$	f_H^7	1.71323
4	$m_{d=2}[LBP_{8-N}^{(x,y,z)}]$	f_H^{12}	1.95193
5	$m_{d=1}[LBP_{8-N}^{(L,U,V)}]$	f_H^3	2.16985
6	$m_{d=5}[LBP_{8-N}^{(A,C1,C2)}]$	f_H^3	2.30183
7	$m_{d=4}[LBP_{8-N}^{(A,C1,C2)}]$	f_H^3	2.38972
8	$m_{d=1}[LBP_{8-N}^{(x,y,z)}]$	f_H^{12}	2.47612
9	$m_{d=5}[LBP_{8-N}^{(r,g,b)}]$	f_H^7	2.54701
10	$m_{d=1}[LBP_{8-N}^{(A,C1,C2)}]$	f_H^5	2.6206

We stop the iterative procedure at $s = 10$ and consider the 10-dimensional most discriminating feature space constitued by the first ten selected features to classify test images, since this is with this dimension that we obtain the best classification result.

D. Classification results

The rate of well-classified images obtained by considering the 10-dimensional feature space above determined reaches **85.6%** by classifying test images with a $k = 7$ nearest neighbor classifier. Since the textures present in the BarkTex database are quite difficult to be discriminated, our method of color texture classification provides very encouraging results. Indeed, the best classification result obtained with this benchmark database is 87%, with a 15-dimensional feature space, composed of features extracted from sum and difference histograms, and a leaving-one-out classification scheme [22].
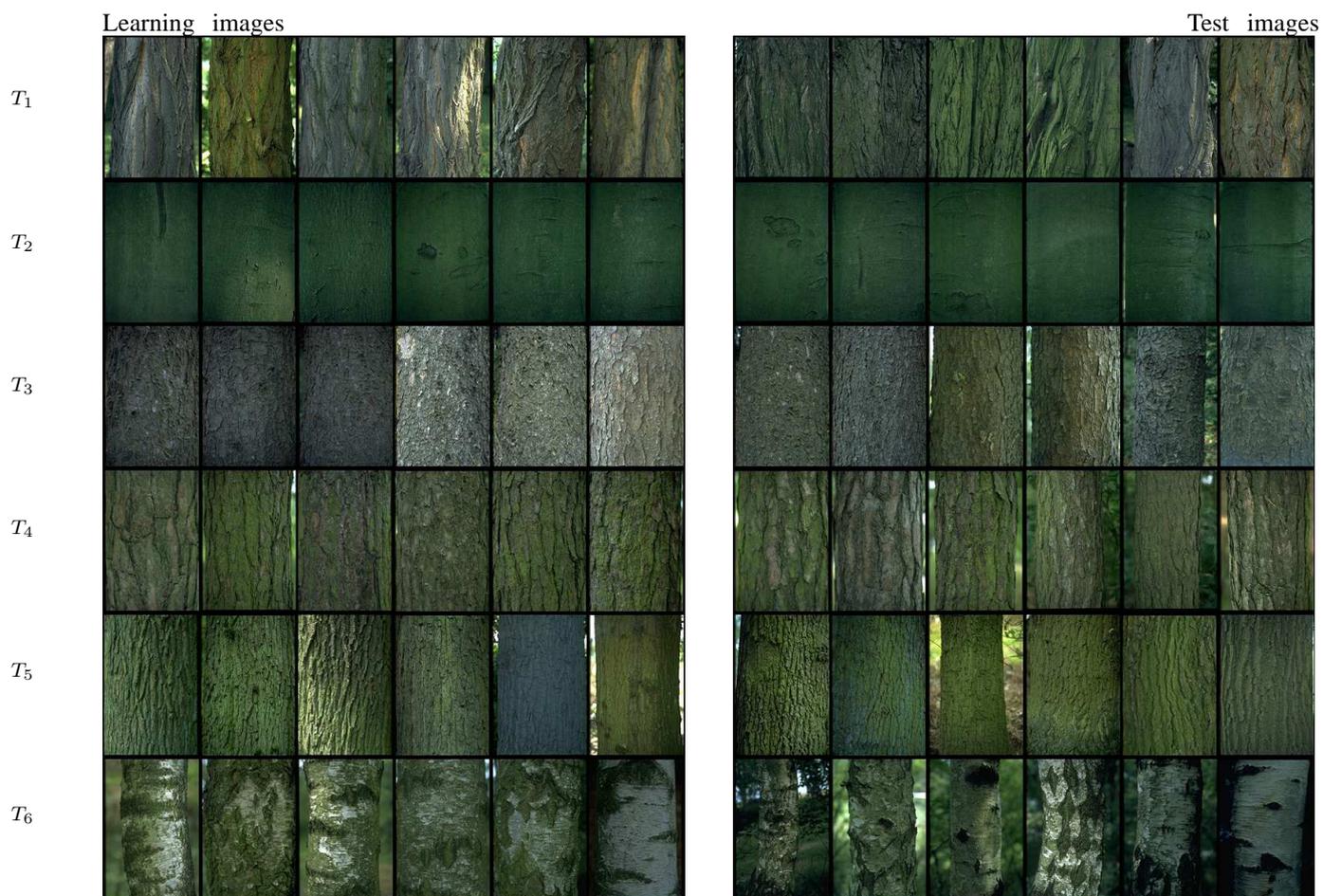
T_1

T_2

T_3

T_4

T_5
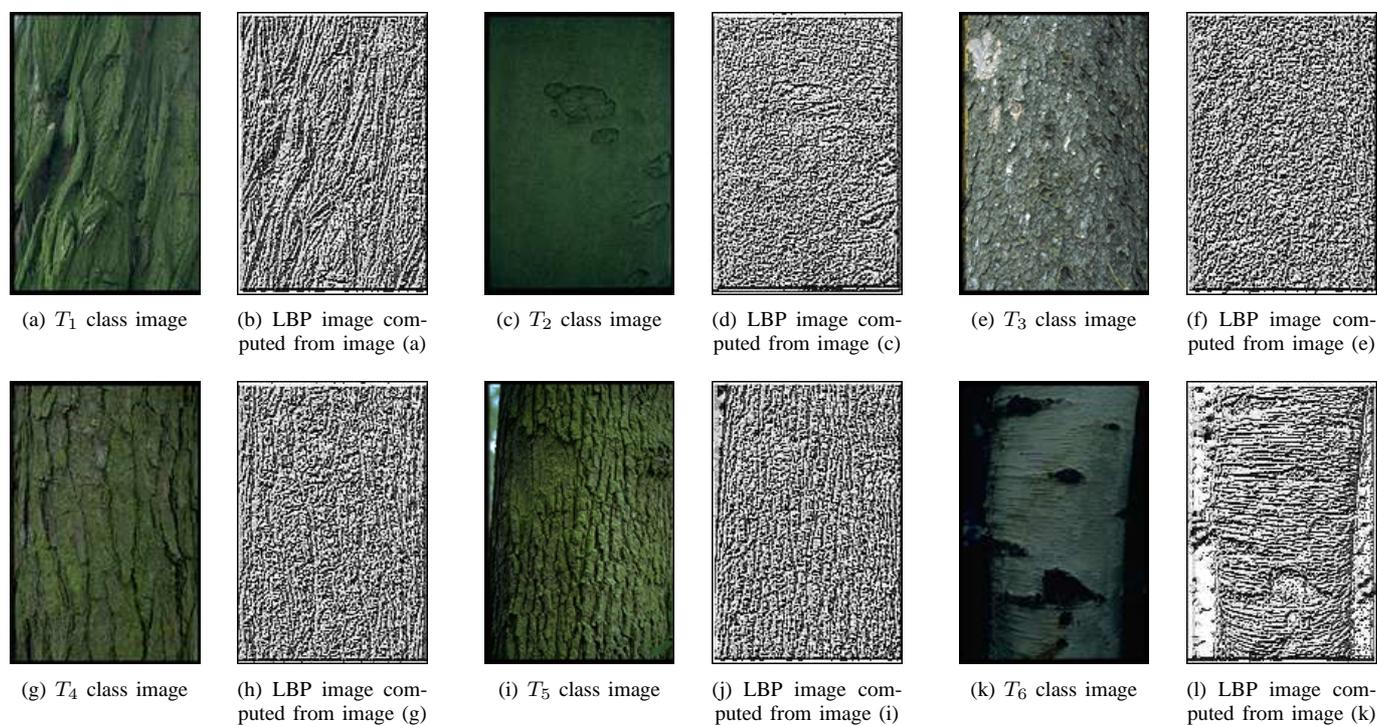
T_6

Fig. 7.   Examples of BarkTex images

(a) T_1 class image

(b) LBP image computed from image (a)

(c) T_2 class image

(d) LBP image computed from image (c)

(e) T_3 class image

(f) LBP image computed from image (e)

(g) T_4 class image

(h) LBP image computed from image (g)

(i) T_5 class image

(j) LBP image computed from image (i)

(k) T_6 class image

(l) LBP image computed from image (k)

Fig. 8.   Color texture images of the BarkTex database and their associated LBP images.

In order to show the interest to associate different color spaces, we have compared the previous rate with the result obtained by considering images only coded in the (R, G, B) space. The best classification result obtained with the Haralick features extracted from co-occurrences matrices computed from LBP images coded in the single (R, G, B) space reaches 72.7%. This rate is obtained by considering the 8-dimensional most discriminating feature space selected by the iterative selection procedure, and the $k = 7$-nearest neighbor classifier. This experiment confirms that the association of several color spaces improves the characterization of color textures and consequently the results of texture classification.

VI. CONCLUSION

The originality of this work lies in the use of a new descriptor to characterize color textures, the color LBP images, which differs from the color LBP initially proposed by Mäenpää and Pietikäinen. Indeed, instead of comparing the color components of pixels, we compare their color rank thanks to a partial color order relation based on euclidean distances. This approach allows to consider only one LBP by image instead of nine.

Another originality is to use Haralick features extracted from co-occurrence matrices computed from the color LBP image to test the effectiveness of this descriptor for color texture classification.

Finally, it is more interesting to extract this color LBP image from color texture image coded in 28 different color spaces.

An iterative selection procedure allows then to select among the extracted features, those which discriminate the textures, in order to build a low dimensional feature space.

Experimental results, achieved with BarkTex database, show the interest of this method with which a satisfying rate of well-classified images (85.6%) is obtained, by analysing a 10-dimensional feature space.

The perspectives of this work are firstly to find an efficient stopping criterion for the iterative selection procedure, then to determine the number k of neighbors used to classify test images and finally, to evaluate the relevance of the color order relation.

Currently, we apply our approach to control the quality of decorated glasses which can present defects on color texture areas.

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