# Compact Color Texture Representation by Feature Selection in Multiple Color Spaces

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Abstract: This paper presents a compact color texture representation based on the selection of features extracted from different configurations of descriptors computed in multiple color spaces. The proposed representation aims to take simultaneously into account several spatial and color properties of different textures. For this purpose, texture images are coded in five different color spaces. Then, texture descriptors with different neighborhood and quantization parameter settings, are calculated from this images in order to extract a high dimensionality feature vector describing the textures. Compact representation is finally obtained by means of a feature selection scheme. Our approach is applied with two well-known color texture descriptors for the classification of three benchmark image databases.

## 1 INTRODUCTION

Texture classification is one of the most complex process in computer vision and image processing. It has been an active topic of research for many years and an important step in many applications such as content based image retrieval, medical image analysis, face recognition, machine vision and many more (Liu et al., 2018). Texture classification is typically categorized into two sub-problems of representation and decision. Texture representation is a fundamental step of texture analysis that consists in extracting features that describe texture information. Texture information refers to the spatial organization of a set of basic elements that requires the analysis of a neighborhood and depends on observation conditions (illumination, field of view, spatial resolution, orientation, viewpoint, deformation, etc). In order to deal with texture appearance variations caused by the change of these conditions, numerous texture descriptors have been proposed in the last decades, firstly for gray level images. Liu et al. proposed an updated survey of advances in texture representation based on Bag of Words (BoW) and on Convolutional Neural Network (CNN) (Liu et al., 2018). Although CNN-based methods have provided impressive performances last years, they suffer from the difficulty to understand the representation that they generate. The choice of the adequate descriptor for classifying textures is therefore a crucial but difficult problem, being agree that classification results depend on the choice of the texture features as well as the tuning of their parameters.

In addition, many studies have proved that the use of color impacts the discrimination of textures and improves classification accuracy (Alvarez and Vanrell, 2012; Khan et al., 2015). That is why many texture descriptors, like Gray Level Cooccurrence Matrix (GLCM), Local Binary Pattern (LBP) and others, were extended to color. These descriptors combine spatial and color information to generate color texture features following two main approaches depending on whether they are considered jointly or independently (Mäenpää and Pietikäinen, 2004; Bianconi et al., 2011). There is a wide variety of color spaces that belong to different families depending on their properties. It is known that the choice of the color space impacts texture classification results too but the prior determination of a suitable color space is a complex problem (Bello-Cerezo et al., 2016; Cernadas et al., 2017).

Many authors propose to combine various texture descriptors in several color spaces in order to take into account their different properties (Khan et al., 2015; Cusano et al., 2016). Because these approaches generate high-dimensional features spaces, they suffer from the curse of dimensionality and require to ex-



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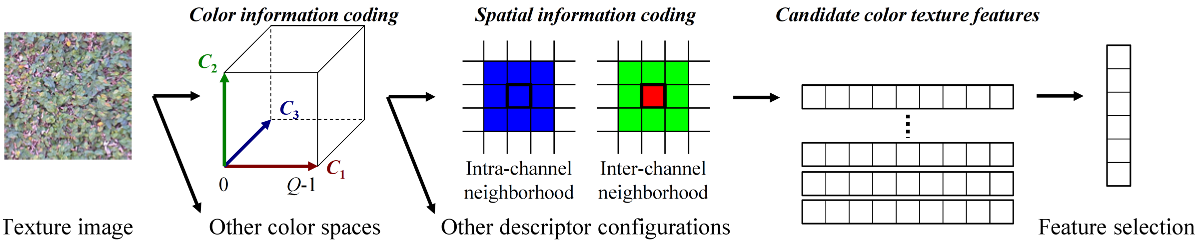


Figure 1: Compact color texture representation.

tract a limited number of relevant features in order to provide compact texture representations that improve classification performance in terms of accuracy and processing time (Porebski et al., 2013b). In most of these works, the parameter settings of the used descriptors, including the chosen color space, are *a priori* predefined. However, the properties of the textures of different classes may be so different that they require to be represented with different descriptor configurations. At the same time, texture representation has to take into account possible intraclass property variations due to changes in illumination, rotation, scale, shape, etc.

In this paper, we propose a compact color texture representation where texture features are computed and selected from different configurations of a same descriptor in multiple color spaces (see figure 1). The proposed approach is applied with two well-known color descriptors that process spatial and color information jointly: Reduced Size Chromatic Cooccurrence Matrix (RSCCM) (Palm, 2004) and Extended Opponent Color Local Binary Pattern (EOCLBP) (Pietikäinen et al., 2011). Intra-channel and inter-channel neighborhoods are both used to extract color texture features from these descriptors. For the first descriptor, Haralick features are extracted from different configurations of RSCCM. For the second one, we propose to extract statistical features from histograms of many color LBP configurations. The extraction of features proposed for this latter descriptor is original because it differs from the classical approaches that use the bins of LBP histograms as texture features and so, it limits the number of candidate features. Another original contribution is to represent a color texture by combining features from several configurations of a same descriptor in order to take advantage of their different spatial and color properties simultaneously. The proposed approach thus overcomes the difficulty of choosing a relevant descriptor configuration and aims to provide a comprehensible and interpretable representation of textures.

The second section of this paper presents the importance of color spaces used in texture classification problems. The two descriptors used in this paper for illustrating our approach are presented in the third section. Section four presents how a compact representation is determined from texture features extracted from a descriptor. Experimental results on three benchmark databases are presented in the fifth section. The last section offers different perspectives for future work in order to improve our approach.

## 2 COLOR SPACES

The color of pixels can be represented in different color spaces which respect different physical, physiologic, and psycho-visual properties. They can be categorized into four families: the primary spaces, the luminance-chrominance spaces, the perceptual spaces and the independent color component spaces (Porebski et al., 2013b).

Since the choice of a color space impacts directly the classification results, many authors tried to compare results obtained by using different color spaces in order to find the most suited one for a given application (Mäenpää and Pietikäinen, 2004; Bello-Cerezo et al., 2016; Cernadas et al., 2017). The synthesis of these works shows that there is no color space well suited to represent all types of textures. To solve this problem, few studies propose multi-color space approaches (Porebski et al., 2018). They exploit the properties of multiple color spaces simultaneously by combining them and overcomes the difficulty of choosing a single relevant color space. Although these approaches have shown their relevance with variable numbers of considered color spaces, it appears that a limited number of color spaces representative of each family is sufficient to improve classification performances. Moreover, many of these spaces require to know the properties of the illumination and the acquisition device. That is why we propose to describe textures with only five color spaces that do not need this knowledge: the *RGB* acquisition image color space with one color space of each family: *YCbCr* luminance-chrominance space, *I1I2I3* independent color component space, *HSV* perceptual space and $RGB_n$ normalized primary space.

# 3 TEXTURE DESCRIPTORS

In this paper, we propose to apply our approach with two popular and efficient texture descriptors: the cooccurrence matrix and the LBP operator known for their computational simplicity.

## 3.1 Haralick Features Extracted from Chromatic Cooccurrence Matrices

### 3.1.1 Chromatic Cooccurrences Matrices

This descriptor is the extension to color of the GLCM operator that is considered as a two-dimensional histogram of pairs of neighbor pixels. An important property of this operator is its invariance to orientation changes. Chromatic Cooccurrence Matrix (CCM) considers both the spatial interactions within and between the color components of neighbor pixels in the image plane and the color distribution in a color space (Palm, 2004).

Let $Q$, be the number of levels used to quantify the color components $C_1$, $C_2$ and $C_3$ of a given color space. A Reduced Size Chromatic Cooccurrence Matrix (RSCCM) is a $Q \times Q$ CCM, where the parameter $Q$ is reduced in order to decrease the memory storage cost and so, the time required to extract texture features from these matrices (Porebski et al., 2013b).

The normalized RSCCM $m_{\mathcal{N}}^{C_k,C_{k'}}[I]$ measures the spatial interactions in the neighborhood $\mathcal{N}$ between the two color components $C_k$ and $C_{k'}$ of an image $I$ ($k,k' \in \{1,2,3\}$). The neighborhood $\mathcal{N}$ is a second parameter defined by the user.

For an image coded in a color space $C_1C_2C_3$ with a quantization level $Q$ and a given neighborhood $\mathcal{N}$, six normalized RSCCM are computed: three within-component matrices ($k = k'$) and three between-component matrices ($k \neq k'$) where $m_{\mathcal{N}}^{C_k,C_{k'}}[I]$ and $m_{\mathcal{N}}^{C_{k'},C_k}[I]$ are symmetric.

### 3.1.2 RSCCM Configurations

Before calculating a chromatic cooccurrence matrix, a number of parameters have to be set and adjusted. This configuration is complex when the color and spatial properties of the analyzed textures are heterogeneous. It principally depends on:

- $Q$, the image quantization level that defines the size of the RSCCM,
- $\mathcal{N}$, the pixel neighborhood in which cooccurrences are counted. $\mathcal{N}$ is controlled by two other parameters:
  - the neighborhood direction: four 2-directional neighborhoods are usually used to compute direction-dependent cooccurrence matrices: 0°, 45°, 90° and 135°. In order to take simultaneously into account all the possible directions of an observed texture, an isotropic $3 \times 3$ neighborhood is generally used with a number of 8 neighbors located in the 4 directions.
  - the neighborhood distance: this distance, denoted $D$, is the spatial infinity-norm distance separating each pixel from its neighbors.

We propose to adjust RSCCM configurations depending on two parameters: the quantization level $Q$ and the neighborhood distance $D$ since we believe these two parameters control the representation of texture acquired with different observation conditions. Haralick features are so extracted from each of the following RSCCM configurations $(D,Q)$:

| | | | | |
|---|---|---|---|---|
| (1, 16) | (1, 32) | (1, 64) | (1, 128) | (1, 256) |
| (2, 16) | (2, 32) | (2, 64) | (2, 128) | (2, 256) |
| (3, 16) | (3, 32) | (3, 64) | (3, 128) | (3, 256) |
| (5, 16) | (5, 32) | (5, 64) | (5, 128) | (5, 256) |
| (10, 16) | (10, 32) | (10, 64) | (10, 128) | (10, 256) |

### 3.1.3 Haralick Features Extracted from RSCCM

The cooccurrence matrices are able to represent the texture but they are not directly used for color texture classification purposes because of the large amount of information they contain. To reduce it while preserving the relevance of these descriptors, Haralick proposed statistical features that can be extracted from each matrix (Palm, 2004). We propose to use the first 13 Haralick features: homogeneity, contrast, correlation, variance, inverse difference moment, sum average, sum entropy, entropy, difference variance, difference entropy and measures of correlation I and II.

A color texture is then represented by Haralick features extracted from RSCCM with different configurations and computed from images coded in multiple color spaces.

## 3.2 Texture Features Extracted from Color LBP Histograms

### 3.2.1 Color LBP Histogram

Color LBP are extensions to color of the Local Binary Pattern operator that captures the local texture properties of a gray level image (Pietikäinen et al., 2011). An important property of this operator is its invariance to monotonic gray-scale changes caused, for example, by illumination variations. In order to characterize the whole color texture image, the LBP operator is applied on each pixel and for each pair of components in the color space $C_1C_2C_3$. Considering a pair of component $(C_k, C_{k'})$, $(k, k' \in \{1,2,3\})$, the color LBP labels a pixel with the component $C_k$ by thresholding its neighborhood $\mathcal{N}$ in the component $C_{k'}$ and by encoding the result as a binary number.

The consideration of the Extended Opponent Color LBP (EOCLBP) operator gives rise to nine LBP images: three within-component LBP images ($k = k'$) and six between-component ($k \neq k'$). These images are usually not exploited directly and most of authors prefer to use LBP histograms and consider histogram bins as texture features (Pietikäinen et al., 2011).

Instead of using the bins of EOCLBP histograms, we propose to extract two different types of statistical features from these histograms. In order to characterize textures acquired with different observation conditions, these features are extracted from many EOCLBP configurations.

#### 3.2.2 EOCLBP Configurations

Due to its popularity, many variants of the basic LBP operator, like the rotation invariant LBP or the uniform LBP for feature dimensionality reduction, as well as their few extensions to color, have been proposed the last two decades (Pietikäinen et al., 2011).

The definition of the original LBP operator with its $3 \times 3$ neighborhood has then been generalized by using a circular neighborhood $\mathcal{N}$ defined by:

- $P$, the number of neighbor pixels that determines the dimensionality of the LBP histograms. For example, a $3 \times 3$ neighborhood with $P = 8$ neighbors gives rise to a $2^8 = 256$-dimensional LBP histogram. For each pair of color components, a color texture is thus described by a $2^P$-dimensional histogram.
- $R$, the distance between each pixel and its neighbors. This distance is equal to the radius of the circle around the central pixel. Generally, when a neighbor pixel is not confused with the circle, a bi-linear interpolation is used to estimate its location. Here, the neighborhood is thus pre-sampled.

With these two parameters, many LBP configurations are available in order to characterize textures in different scales. In this paper, we propose to consider the following EOCLBP configurations $(P, R)$:

| | | | | |
|---|---|---|---|---|
| (8, 1) | (8, 2) | (8, 3) | (8, 5) | (8, 10) |
| | (16, 2) | (16, 3) | (16, 5) | (16, 10) |
| | | (24, 3) | (24, 5) | (24, 10) |

#### 3.2.3 Statistical Features Extracted from EOCLBP Histograms

With the EOCLBP operator, a color texture is represented by 9 LBP histograms that are concatenated to constitute a vector containing $9 \times 2^P$ features for a given color space $C_1C_2C_3$. Several approaches have been proposed to reduce the dimensionality of such a feature space, like the uniform LBP operator. Some authors select the most discriminant bins that constitute the LBP histograms (Pietikäinen et al., 2011). Others authors reduce the number of histograms with only the three within-component LBP histograms or by adding only three out of six between-component LBP histograms, assuming that the opponent pairs such as $(C_1, C_2)$ and $(C_2, C_1)$ are highly redundant (Mäenpää and Pietikäinen, 2004). Another approach consists in selecting, out of the nine LBP histograms, the most discriminant ones for the considered application (Porebski et al., 2018).

In this paper we propose to extract statistical features from each LBP histogram and concatenate them to form a reduced dimensionality statistical feature vector. For this purpose, two types of statistical features are proposed:

- 7 first order statistical features: mean, median, mode, standard deviation, symmetry around the average and two inter quartile ranges.
- 11 second order statistical features extended from the first 11 Haralick features presented in section 3.1.3 and adapted to deal with histograms.

We propose to extract these 18 features from histograms of different EOCLBP configurations for representing color textures.

## 4 COMPACT COLOR TEXTURE REPRESENTATION

Supervised texture classification aims to assign a given texture to one of a set of known texture categories for which training samples have been given. This process is divided into two successive stages: a learning stage in which a classifier is trained and a decision stage in which this classifier operates. During the learning stage, texture images are represented by descriptors from which texture features are extracted. The extraction of discriminant texture features plays an essential role in the success of the classification. So the learning stage has to provide a powerful texture representation for the decision stage.

The previously proposed descriptors are able to take into account the heterogeneity of color textures to be analyzed. However, they tend to produce high dimensionality feature vectors, especially when the number of configurations increases or when it is applied to color images. It is well-known that the performance of a classifier is generally dependent on the dimension of the feature space due to the curse of dimensionality. Thus, dimensionality reduction methods are needed to reach satisfying classification accuracies while decreasing the memory storage and the computation time.

To reduce the dimensionality of the feature space, two main strategies are proposed: feature extraction and feature selection. Because feature extraction methods require the computation of all candidate features during the decision stage to build the new low-dimensional feature subspace, they are time-consuming. So, feature selection methods that just require the computation of a reduced number of selected features are preferred here.

So, the proposed compact color texture representation consists in selecting the most discriminant color texture features among a set of candidate ones during a learning stage.

## 4.1 Candidate Color Texture Features

### 4.1.1 Features Extracted from Multiple RSCCM Configurations

In order to take advantage of the specific properties of several color spaces simultaneously, each image is first coded in 5 color spaces described in section 2. Then, for each of the 25 RSCCM configurations described in subsection 3.1, 6 RSCCM are computed and the 13 Haralick features are extracted from each RSCCM.

Using Haralick features extracted from different RSCCM configurations, a color texture is firstly represented by $5 \times 25 \times 6 \times 13 = 9750$ candidate features.

### 4.1.2 Features Extracted from Histograms of Multiple EOCLBP Configurations

To extract statistical features from histograms of multiple EOCLBP configurations, each image is first coded in 5 color spaces descried in section 2. Then, for each of the 12 EOCLBP configurations described in subsection 3.2, 9 LBP images are computed and 18 statistical features are extracted from each EOCLBP histogram.

Using statistical features extracted from EOCLBP histograms, a color texture is firstly represented by $5 \times 12 \times 9 \times 18 = 9720$ candidate features.

## 4.2 Feature Selection

Many authors have chosen to use sequential feature selection methods in order to build a reduced dimension feature subspace during the learning stage of the classification process. Porebski et al. were among the first to use sequential forward selection (SFS) scheme to select the most discriminant Haralick features extracted from cooccurrence matrices of images coded in 28 different color spaces (Porebski et al., 2013b).

Because these scheme have shown their efficiency, a SFS scheme is applied in this paper for a compact representation of color textures. SFS scheme is a bottom-up approach that starts with an empty set and adds features at each step of the procedure in order to constitute candidate feature subspaces to be evaluated. An evaluation function then measures the capacity of the feature subspaces built during the generation step to correctly classifying the given textures and selects the most discriminant subspace. The procedure continues until a stopping criterion is satisfied.

In order to highlight the interest of our approach, a wrapper model evaluates each candidate feature subspace by using the classification accuracy as the evaluation function in a supervised context. In this context, wrapper models require to split up the initial image database to a training, a validation, and a testing image subset, according to a holdout partition. At each step $s$ of this procedure, the classification accuracy $C_s$ is measured with the validation image subset in order to evaluate the discriminant power of each candidate subspace. The candidate subspace with the highest accuracy is selected as the most discriminant $s$-dimensional subspace. In this paper, the classification accuracy is estimated as the percentage of the validation images that have been correctly classified by the nearest neighbor classifier because of its parameter-independence and its simplicity of implementation. Although the wrapper model is time-consuming and classifier-dependent, it gives good results and easily determines the dimensionality of the feature subspace by searching the best classification accuracy. The procedure runs until the dimensionality of the selected feature space reaches a maximum value $s_{max}$ equal to 100 in our experiments. The dimensionality $\hat{s}$ of the finally selected subspace is equal to the iteration step for which the classification accuracy is maximum.

In order to select uncorrelated color texture features, correlation levels between all candidate features are measured before performing the SFS scheme. In our approach, candidate features are considered as redundant if their correlation measure is greater than a threshold equal to 0.95 and are thus removed.

# 5 EXPERIMENTS

In order to evaluate the efficiency of our approach, we perform an evaluation on the three well known and largely used benchmark color texture databases Outex-TC-00013[1], NewBarkTex[2] and USPtex[3].

Each database has been chosen to measure the relevance of our approach by comparing the classification accuracies with those of previous works under the same experimental protocol (number of classes, size of images, number of images for each class, total number of images, and accuracy evaluation method). They are representative of different color texture classification problems with different numbers of classes as shown in table 1

Table 1: Experimented texture databases.

| Dataset | Image size | #classes | #images |
|---|---|---|---|
| Outex-TC-00013 | $128 \times 128$ | 68 | 1360 |
| NewBarkTex | $64 \times 64$ | 6 | 1632 |
| USPtex | $128 \times 128$ | 191 | 2292 |

Let us note that the considered databases are given with only two image subsets according to a holdout evaluation method: half of the images defines a training subset and the other half a testing subset. However, our approach needs three subsets because it uses a wrapper model associated to the nearest neighbor classifier for the feature selection scheme. For comparison with other works, this classifier has to use the same training subset. We thus propose to use the testing subset as a validation subset and to consider that the classification accuracies are measured during the feature selection scheme of the learning stage. Therefore, the classification results can be interpreted as optimistic but they can be compared with other works using the same split into training and testing subsets.

## 5.1 Experimental Results

### 5.1.1 Haralick Features Extracted from Different RSCCM Configurations

Table 2 presents results obtained with the proposed approach using a combination of Haralick features extracted from the multiple RSCCM configurations proposed in section 3.1.

In addition, this table shows the results obtained in multiple color spaces with only one predefined configuration. As mentioned by Porebski et al., when $Q = 16$ and $D = 1$, RSCCM analysis reaches satisfying classification results while significantly reducing the processing time (Porebski et al., 2013b).

Table 2: Classification accuracies for different RSCCM configurations in multiple color spaces.

| Dataset | $(D,Q)$ | $C_{\hat{s}}$ | $\hat{s}$ |
|---|---|---|---|
| Outex-TC-00013 | multiple | 98.53 | 29 |
| | $(1,16)$ | 97.20 | 33 |
| NewBarktex | multiple | 86.39 | 75 |
| | $(1,16)$ | 84.50 | 93 |
| USPtex | multiple | 98.87 | 38 |
| | $(1,16)$ | 95.98 | 54 |

This table highlights the interest of our approach that produces higher classification accuracies with lower dimensionality feature spaces compared to a predefined descriptor configuration.

### 5.1.2 Statistical Features Extracted from Different EOCLBP Configurations

Table 3 presents results obtained with the proposed approach using a combination of statistical features extracted from histograms of the multiple EOCLBP configurations proposed in section 3.2.

In addition, this table shows the results obtained in multiple color spaces with only one predefined configuration. We choose to use the original LBP configuration with $P = 8$ and $R = 1$ in two cases: without and with a bin selection (BS) scheme (Pietikäinen et al., 2011).

Table 3: Classification accuracies for different EOCLBP configurations in multiple color spaces.

| Dataset | $(P,R)$ | $C_{\hat{s}}$ | $\hat{s}$ |
|---|---|---|---|
| Outex-TC-00013 | multiple | 96.91 | 18 |
| | $(8,1)$ | 96.61 | 47 |
| | $(8,1)$ with BS | 97.50 | 75 |
| NewBarktex | multiple | 89.82 | 20 |
| | $(8,1)$ | 89.46 | 66 |
| | $(8,1)$ with BS | 86.76 | 66 |
| USPtex | multiple | 97.64 | 18 |
| | $(8,1)$ | 96.71 | 49 |
| | $(8,1)$ with BS | 93.45 | 41 |

This table shows that our approach provides representations with a lower dimensionality than the other approaches and with a bit higher classification accuracies. Moreover, statistical features extracted from EOLBP histograms give comparable results than classical bin selection approach with a lower dimensionality feature space too. This result underlines the relevance of this original LBP representation.

[1]available at: http://www.outex.oulu.fi/index.php?page=classification#Outex_TC_00013
[2]available at: https://www-lisic.univ-littoral.fr/~porebski/BarkTex_image_test_suite.html
[3]available at: https://www-lisic.univ-littoral.fr/~porebski/USPtex_image_set.html

Table 4: Comparison between the classification accuracies reached with the 1-NN classifier.

| Dataset | Descriptor | Color space | Accuracy |
|---|---|---|---|
| Outex-TC-00013 | Our approach with RSCCM | 5 color spaces | 98.5 |
| | Our approach with EOCLBP | 5 color spaces | 96.9 |
| | (Porebski et al., 2013b) | 28 color spaces | 96.6 |
| | (Porebski et al., 2018) | 9 color spaces | 95.6 |
| | (Mäenpää and Pietikäinen, 2004) | *HSV* | 95.4 |
| | (Qazi et al., 2011) | *IHLS* | 94.5 |
| | (Alvarez and Vanrell, 2012) | *RGB* | 94.1 |
| NewBarkTex | Our approach with EOCLBP | 5 color spaces | 89.8 |
| | Our approach with RSCCM | 5 color spaces | 86.4 |
| | (Porebski et al., 2018) | 9 color spaces | 88.0 |
| | (Kalakech et al., 2018) | *RGB* | 81.4 |
| | (Porebski et al., 2013a) | *RGB* | 81.4 |
| | (Ledoux et al., 2016) | *RGB* | 77.7 |
| | (Porebski et al., 2014) | *RGB* | 75.9 |
| USPtex | Our approach with RSCCM | 5 color spaces | 98.9 |
| | Our approach with EOCLBP | 5 color spaces | 97.6 |
| | (Porebski et al., 2018) | 9 color spaces | 97.6 |
| | (Liu et al., 2017) | *RGB* | 95.9 |
| | (Guo et al., 2016) | *RGB* | 93.9 |
| | (Kalakech et al., 2018) | *YUV* | 93.2 |
| | (Ledoux et al., 2016) | *RGB* | 84.2 |

## 5.2 Comparisons and Discussion

Table 4 reports the classification results reached by other method applied on the three experimented benchmark datasets with the same experimental protocol. In order to achieve classifier-independent comparisons, only the five better texture classification results reached with the nearest neighbor classifier (1-NN) and the same training subset are presented.

As we can notice, the results obtained by our approach is competitive with other approaches and are very promising. Obviously, other results with other classifiers and other protocols are available in the literature (Cernadas et al., 2017; Bello-Cerezo et al., 2016). This table also confirms that multi-color space approaches outperform approaches using a single color space. For the Outex-TC-00013 and USPtex datasets, the best result is reached by our approach with RSCCM whereas for the NewBarkTex dataset, it is reached by EOCLBP. So, none of these descriptors is more relevant than the other.

## 5.3 Processing Time

### 5.3.1 Learning Stage

Table 5 compares the processing time required by the learning stage of 1360 images of the Outex-TC-00013 image test suite, for both training and testing images. These times are obtained using Matlab software on a PC cadenced at 2.00 GHz and with 4 MB RAM.

Table 5: Processing time of the learning stage for the 1360 training and testing images of the Outex-TC-00013 dataset.

| Descriptor | RSCCM | EOCLBP |
|---|---|---|
| Feature computation | 287 800 s | 1 369 240 s |
| Feature selection | 10 911 s | 9 266 s |
| Total | 289 711 s | 1 378 506 s |

The learning stage seems time-consuming because a wrapper model is used here to select color texture features. With this model, the classification of all validation images is needed in order to estimate the classification accuracy for each candidate subspace and to determine the dimension of the feature subspace under construction. The solution to this problem is to prefer filter or embedded models for the feature selection evaluation in future work.

The learning time required with the EOCLBP descriptor is high because of the computation of features extracted from the configuration using $P = 24$ neighbors which consumes the most part of this time. Indeed, with this parameter value, $2^{24} = 16\ 777\ 216$-dimensional histograms are analyzed.

### 5.3.2 Decision Stage

Table 6 shows the processing time required in order to classify a $128 \times 128$ Outex sub-image. This time depends on the selected color texture features and the dimensionality of the feature space.

This table shows that the classification time is very low for RSCCM compared to EOCLBP because of the analysis of high dimensional histograms when the number of neighbors is high.

Table 6: Processing time of the decision stage for one $128 \times 128$ testing image of the Outex-TC-00013 dataset.

| Descriptor | RSCCM | EOCLBP |
|---|---|---|
| Feature computation | 933 ms | 3 000 ms |
| Classification | 3 ms | 3 ms |
| Total | 936 ms | 3 003 ms |

# 6 CONCLUSION

In this paper, we have proposed a compact color texture representation based on the combination of texture features extracted from various configurations of descriptors in multiple color spaces. This representation takes into account different color and spatial properties of the textures to be analyzed and overcomes the difficulty of a prior parameter settings. In addition, a novel family of features computed from histograms of LBP has been proposed in this paper.

Compared to others approaches, experiments carried out on three benchmark texture databases give competitive results that are very promising for future work. The proposed approach should be improved by using a filter model for feature selection rather than the wrapper model chosen in this paper. Since filter model is classifier-independent, it should greatly reduce the execution time of the learning stage. For the decision stage, it would be interesting to apply more performing classifiers like SVM.

Finally, in order to increase the classification accuracies, we plan to extend our approach to the combination of texture features extracted from manifold descriptors (RSCCM, EOCLBP and others) with different configurations and several color spaces.

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