ITERATIVE FEATURE SELECTION FOR COLOR TEXTURE CLASSIFICATION

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ABSTRACT

In this paper, we describe a new approach for color texture classification by use of Haralick features extracted from color co-occurrence matrices. As the color of each pixel can be represented in different color spaces, we automatically determine in which color spaces, these features are most discriminating for the textures. The originality of this approach is to select the most discriminating color texture features in order to build a feature space with a low dimension. Our method, based on a supervised learning scheme, uses an iterative selection procedure. It has been applied and tested on the BarkTex benchmark database.

***Index Terms*—** image color analysis, feature extraction, image texture analysis, image classification.

1. INTRODUCTION

For the industrial quality control and scene analysis purposes, color textures have to be characterized in order to classify images. However, a few of color texture analysis tools are available. Since many authors have shown that the use of color improves the results of texture classification, most of the color texture feature are deduced from tools designed for grey level images [1, 2, 3, 4].

The color of each pixel is characterized by its three trichromatic components R, G and B. The analysis of the pixel color distribution in a color space is not restricted to the (R, G, B) color space. Indeed there exists a large number of color spaces which respect different physical, physiological and psychological properties. The performance of an image segmentation procedure is known to depend on the choice of the color space [5, 6]. In this paper, we study the impact of the choice of the color space on the performance reached by an algorithm of texture classification. For this purpose, textures are characterized by Haralick features extracted from color co-occurrence matrices which are computed in different color spaces.

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Thus, with these Haralick features, Palm builds a 96-dimensional feature space to characterize textures in the (R, G, B) and (L, U, V) color spaces [2]. Although the results given by this approach are great, the dimension of this feature space should be reduced to decrease the processing time. So, we propose to measure the discriminating power of the extracted color texture features, in order to build a feature space with a low dimension.

In the second section of this paper, we present the color space influence on texture analysis. Then, we describe the Haralick features extracted from color co-occurrence matrices in the third section. The fourth section details the iterative procedure which selects the most discriminating feature space. Our method, based on a supervised learning, has been applied and tested on the BarkTex benchmark database in the last section.

2. COLOR SPACE AND TEXTURE ANALYSIS

Palm compares the performances reached by several texture features calculated with images coded in different color spaces. He concludes that the (L, U, V) space is better adapted than the (R, G, B) space for the color texture discrimination [2].

A similar approach is adopted by Drimbarean who underlines that the (Y, I, Q) space allows to obtain better results than the (R, G, B) space [3].

Chindaro uses a color texture classification system based on a set of independent classifiers each assigned to a different color space. In order to classify the considered request images, he fuses the classification decision of each classifier. He concludes that the association of informations coming from the different color spaces improve performance [4].

The synthesis of these works does not allow to conclude on the definition of a single color space adapted to color texture analysis. That's why we propose to select the most discriminating texture features of color images coded in 28 different color spaces. 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 figure 1) [5].

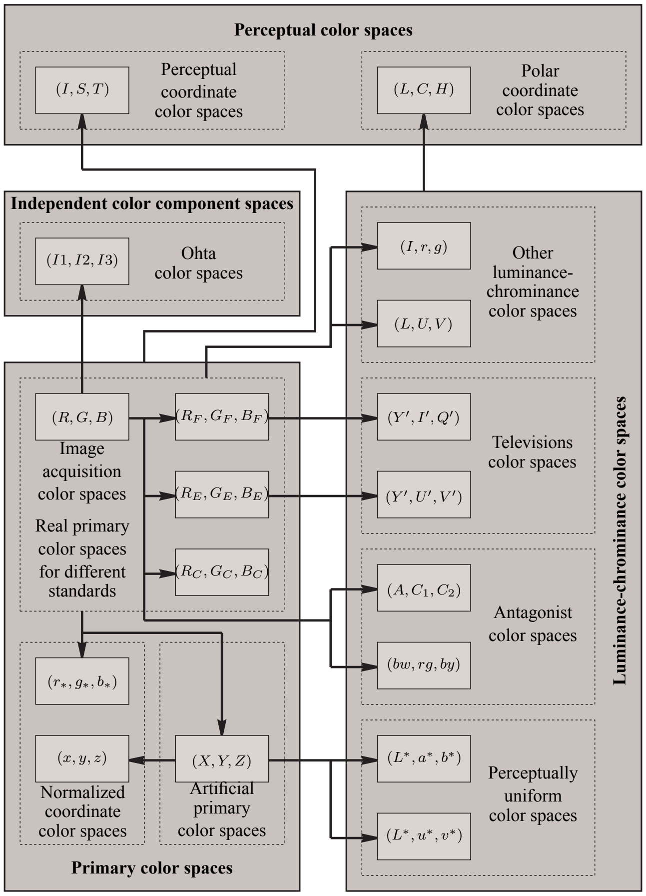

Fig. 1 : Color space families

3. COLOR TEXTURE FEATURES

3.1. Color co-occurrence matrices

Color co-occurrence matrices, introduced by Palm [2], are a statistical feature which both measures the color distribution in an image and considers the spatial interaction between pixels. These matrices are defined for each color space denoted (C_1,C_2,C_3) of figure 1. Let C_k and $C_{k'}$, be two of the three color components of this space ($k, k' \in \{1, 2, 3\}$) and $M^{C_k,C_{k'}}[\mathbf{I}]$, the color co-occurrence matrix which measures the spatial interaction between the components C_k and $C_{k'}$ of the pixels in the image **I**. The cell $M^{C_k,C_{k'}}[\mathbf{I}](i, j)$ of this matrix contains the number of times that a pixel P whose color component value $C_{k'}(P)$ is equal to j, has, in its 3x3 neighborhood, a pixel Q whose color component $C_k(Q)$ is equal to i.

Each color image **I** is characterized by the six following color co-occurrence matrices : $M^{C_1,C_1}[\mathbf{I}]$, $M^{C_2,C_2}[\mathbf{I}]$, $M^{C_3,C_3}[\mathbf{I}]$, $M^{C_1,C_2}[\mathbf{I}]$, $M^{C_1,C_3}[\mathbf{I}]$ and $M^{C_2,C_3}[\mathbf{I}]$. Since the matrices $M^{C_2,C_1}[\mathbf{I}]$, $M^{C_3,C_1}[\mathbf{I}]$ and $M^{C_3,C_2}[\mathbf{I}]$ are respectively symmetric to the matrices $M^{C_1,C_2}[\mathbf{I}]$, $M^{C_1,C_3}[\mathbf{I}]$ and $M^{C_2,C_3}[\mathbf{I}]$, they are not used.

As they measure the local interaction between the pixels, the color co-occurrence matrices are sensitive to significant differences of spatial resolution. To decrease this sensitivity, it is necessary to normalize these matrices by the total co-occurrence number $\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} M^{C_k,C_{k'}}[\mathbf{I}](i, j)$, where N is the quantification level number of the color components. The normalized color co-occurrence matrix $m^{C_k,C_{k'}}[\mathbf{I}](i, j)$ is defined by :

$$m^{C_k,C_{k'}}[\mathbf{I}](i, j) = \frac{M^{C_k,C_{k'}}[\mathbf{I}](i, j)}{\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} M^{C_k,C_{k'}}[\mathbf{I}](i, j)}.$$

The color co-occurrence matrices characterize the color textures in the images. However, they cannot be directly exploited because they contain a large amount of information. To reduce it, while preserving the relevance of these descriptors, we use Haralick features extracted from these matrices.

3.2. Haralick features

Haralick introduces 14 texture features denoted I_1 to I_{14} extracted from co-occurrence matrices [7]. These features are statistical measures on the co-occurrence matrices of an image which allow to reduce the information quantity of each matrix. For example, Palm uses eight of these fourteen Haralick features : homogeneity, contrast, correlation, variance, inverse difference moment, entropy, correlation 1 and 2 [2].

4. FEATURE SELECTION

4.1. Candidate color texture features

For each image coded in a color space, we dispose of 6 color co-occurrence matrices and so of 6×14 Haralick features extracted from these matrices. The number of color spaces used here being equal to 28, we examine $N_f = 6 \times 14 \times 28 = 2352$ candidate color texture features (see. figure 2). Since the total number N_f of candidate 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.

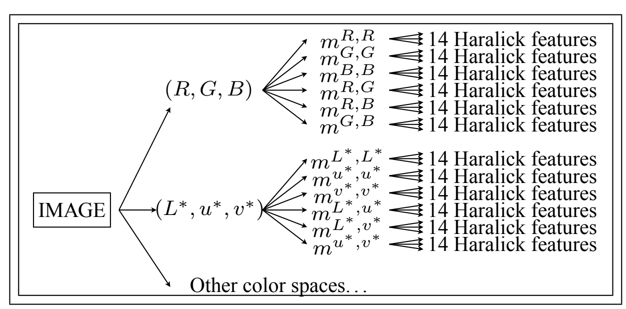

Fig. 2 : Candidate color texture features

4.2. 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 [5].

In a first time, N_ω learning images which are representative of each of the N_T texture classes is interactively selected by the user. This step consists in processing the $N_f = 2352$ color texture features for each learning image. Then, the procedure selects automatically the best features, that is to say those which are the most discriminating for the N_T texture classes thanks to the following iterative selection procedure.

At each step d of this procedure, an informational criterion J is calculated in order to measure the discriminating power of each candidate feature space. At the beginning of this procedure ($d = 1$), 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 is the best one for discriminating the texture classes. It is selected as the first step and is associated in the second step of the procedure ($d = 2$) 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 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 $d \geq 2$ of the procedure, the correlation between each of the available color texture features and each of the $d-1$ other color texture features constituting the selected $d-1$ 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 [5].

We assume that the more the 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 d of the procedure and for each of the $(N_f - d + 1)$ d-dimensional candidate feature spaces, we define, for the i^{th} 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 $X_{i,j} = [x^1_{i,j}, ..., x^d_{i,j}]^{\mathrm{T}}$ where $x^d_{i,j}$ is the d^{th} color texture feature. The measure of compactness of each texture class T_j is defined by the intra-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 $M_j = [m^1_j, ..., m^d_j]^{\mathrm{T}}$ is the mean vector of the d 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 inter-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 $M = [m^1, ..., m^d]^{\mathrm{T}}$ is the mean vector of the d color texture features for all the classes. The most discriminating feature space maximizes the information criterion:

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

There does not exist any efficient measure to compare the discriminating power of two spaces with different dimensions. So, we retain a very simple stopping criterion of this iterative procedure, which is the decreasing of the rate of well-classified learning images. Let us notice that the criterion used to determine the dimension depends on the classification rule. Once the feature space is selected, the request texture images are classified thanks to the nearest mean classifier [5].

5. RESULTS

In order to show the interest of the interative selection procedure, the results obtained with the 28 color spaces are compared with those obtained by only using the (R, G, B) space.

5.1. BarkTex database

Color images of the BarkTex database available at *ftp://ftphost.uni-koblenz.de/outgoing/vision/Lakmann/BarkTex* are equally divided into six tree bark classes (**Betula pendula** (T_1), **Fagus silvatica** (T_2), **Pica abies** (T_3), **Pinus silvestris** (T_4), **Quercus robus** (T_5), **Robinia pseudacacia** (T_6)) with 68 images by class. To build the learning database, we have extracted 32 images of each texture class. The 36 remaining images ($68 - 32 = 36$) are request images. Figure 3 illustrates a subset of learning images on the left and a part of the request images used to test our classification method on the right.

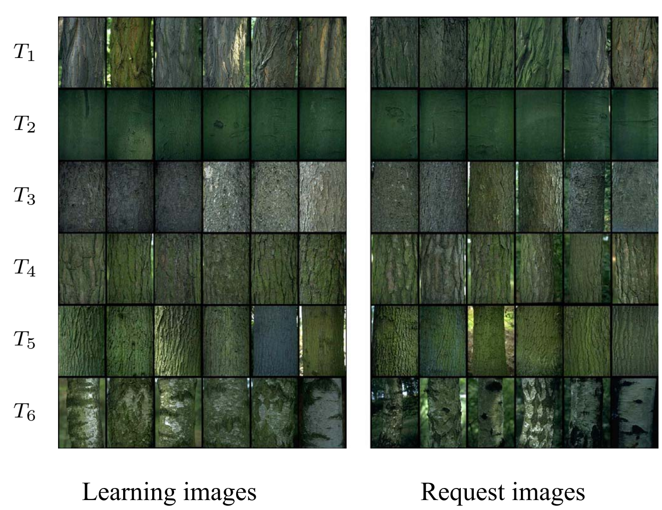

Fig. 3 : BarkTex images

5.2. Selected texture feature space

The supervised learning procedure iteratively selects the most discriminating color texture features.

Iteration step	Haralick feature	Matrix	Color space	Rate of well-classified learning images
1	I_{11}	$m^{B,B}$	(R, G, B)	44.3%
2	I_{10}	$m^{I1,I3}$	$(I1, I2, I3)$	55.7%
3	I_9	m^{L^*,u^*}	(L^*, u^*, v^*)	62.5%
4	I_5	$m^{I,H}$	(I, S, T)	64.6%
5	I_5	$m^{I,I}$	(I, S, T)	70.3%
6	I_2	m^{L^*,a^*}	(L^*, a^*, b^*)	74.5%
7	I_5	$m^{G,B}$	(R, G, B)	70.8%

Table 1 : Texture feature iteratively selected

The table 1 shows that, at the first iteration step, the most discriminating color texture feature which maximises J, is the eleventh Haralick feature I_{11} extracted from the color co-occurrence matrix $m^{B,B}$ calculated in the (R, G, B) space. At the second iteration step, this feature is associated to the feature I_{10} extracted from the color co-occurrence matrix $m^{I1,I3}$ calculated in the ($I1$,$I2$,$I3$) space to constitute the most discriminating two-dimensional feature space with respect to J. Table 1 contains, for each iteration step d of the procedure, the rate of well-classified learning images in the d-dimensional selected feature space. The dimension of the most discriminating feature space is equal to 6 since the rate of well-classified learning images is the highest at the sixth iteration step.

5.3. Classification results

The rate of well-classified request images reaches 76.8% by considering the 6-dimensional feature space above determined. Since the textures present in this database are quite difficult to be discriminated, our method of color texture classification provides very encouraging results. The selection of the Haralick features extracted from the color co-occurrence matrices calculated in 28 different color spaces provides better classification results than those obtained with the single (R, G, B) space (76.8% vs 53.7%). The time required for the selection of the 6 most discriminant color texture features, from the 32 learning images coded in the 28 color spaces, is approximatively of 8 hours for an implementation on a PC cadenced at 2.40 GHz and the classification of each request image requires 2.5 seconds.

Palm obtains a good rate of well classification (86%) but the time required to classify each request image with his method must be very important due to the 96-dimensional feature space. Furthermore, he uses the leaving-one-out method for the classification, which not allows us to directly compare his results to ours. But we can conclude that a carefull selection of color texture features allows to obtain good results with a low number of features. Furthermore, our classification results should be improved by processing directionnal color co-occurrence matrices as Palm has done for discriminating directional textures formed by the tree barks.

6. CONCLUSION

The originality of this work is to select the most discriminating Haralick features extracted from the color co-occurrence matrices calculated in different color spaces in order to build a feature space with a low dimension for texture classification. We have compared our results with those obtained by only using the (R, G, B) space and have shown that the consideration of different color spaces improves significantly the classification quality. Our iterative selection procedure would be generalized to other relevant texture features as wavelets, Gabor filters or Markov random fields.

7. ACKNOWLEDGEMENTS

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