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Hybrid color-texture space for image classification

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Abstract—This work presents an approach for the construction of a hybrid color-texture space by using mutual information. Feature extraction is done by the Laws filter with SVM (Support Vectors Machine) as a classifier. The classification is applied on the VisTex database and a SPOT HRV (XS) image representing two forest areas in the region of Rabat in Morocco. The result of classification obtained in the hybrid space is compared with the one obtained in the RGB color space.

Keywords—Color, texture, laws filter, mutual information, SVM, hybrid space.

I. INTRODUCTION

IN the literature, color and texture analysis was largely studied. Each of two domains was used in a separated scheme for the classification of images; however the result obtained is not the best.

Some researchers propose using a combination of color and texture to improve the result of classification. In [1] [2], texture features were first computed in grayscale then combined with color histogram and moments. In [3], the authors classify the image in various color spaces, independently, using the parameter energy to select the space which gives the best rate of good classification. However in these studies the complementarity of the information contained in each space is not exploited. To exploit this complementarity, [4] propose to combine all spaces at once for the construction of a hybrid color space. Other authors [5] [6] complete this study of color by an analysis of texture based on the matrix of co-occurrence. The hybrid color space is constructed by looking for a combination of the parameters which maximizes an evaluation function. The weakness of the approaches presented in [4] [5] [6] is that it is based on a greedy algorithm; such research is costly in time and does not guarantee a global maximum.

The mutual information is widely used in the feature selection in the last years. It has given encouraging results [7]. Our approach consists in using a method of selection developed by [8] [9]. This method based on the extension of the mutual information criterion is used for the construction of the color-texture space adapted to our image.

Our approach have been first applied and tested on the VisTex database, then on a SPOT image.

The remaining of this paper is organized as follows. In section (2) we describe the steps of our global method for constructing the hybrid color-texture space. In section (3), we treat the SVM classifier in brief. The complete results and their comments will be presented in section (4). Finally, in section (5), we end by a conclusion and some perspectives.

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II. HYBRID COLOR-TEXTURE SPACE CONSTRUCTION

A. Color spaces

The construction of the hybrid color-texture space starts with transforming an image, initially represented in the RGB standard system, into different color spaces. Obviously there is a several number of color spaces to represent a color image. They can be divided into four families [4] namely:

- The primary spaces which are based on the trichromatic theory assuming that it is possible to match any color by mixing appropriate amounts of three primary colors.
- The perceptual spaces which try to quantify the subjective human color perception using the intensity, the hue and the saturation.
- The luminance-chrominance spaces where one component represents the luminance and the two others the chrominance.
- The independent axis spaces resulting from different statistical methods which provide as less correlated components as possible.

A global color space C_s gathers the components chosen for our approach, with N_{C_s} =30 vectors:

$$C_s = \{R, G, B, r, g, b, X, Y_1, Z, x, y, z, L, a, b, u_1, v_1, c, h, H, S, V, Y, i, q, u_2, v_2, I_1, I_2, I_3\}$$

The color study is associated with texture analysis, by calculating 2 statistical parameters and 9 parameters of Laws filter.

B. Laws filter

Many methods for texture extraction were proposed in the literature [10] [11] [12]. Among these methods we kept the laws filter for its performance and implementation simplicity [10] [12]. The principle of the laws filter consists in convolving an image bloc with a set of nine 2-D filters. Each filter, called mask, is characterised by a 3x3 matrix of different coefficients [13]. From each nine resulting images, various statistical quantities can be calculated. Laws indicate that the statistics the most useful for the texture discrimination were the squares sums or absolutes values sums of the image after convolution with these masks. He concludes that this method gives noticeably best result than the co-occurrence matrix. The nine masks M_1 to M_9 recommended by Laws are:

$$M_1 = \begin{pmatrix} +1 & +2 & +1 \\ +2 & +4 & +2 \\ +1 & +2 & +1 \end{pmatrix} M_2 = \begin{pmatrix} -1 & 0 & +1 \\ -2 & 0 & +2 \\ -1 & 0 & +1 \end{pmatrix}$$

$$M_3 = \begin{pmatrix} -1 & +2 & -1 \\ -2 & +4 & -2 \\ -1 & +2 & -1 \end{pmatrix} M_4 = \begin{pmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ +1 & +2 & +1 \end{pmatrix}$$

$$M_5 = \begin{pmatrix} -1 & -2 & -1 \\ +2 & +4 & +2 \\ -1 & -2 & -1 \end{pmatrix} M_6 = \begin{pmatrix} +1 & -2 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & +1 \end{pmatrix}$$

$$M_7 = \begin{pmatrix} +1 & -2 & +1 \\ 0 & 0 & 0 \\ -1 & +2 & -1 \end{pmatrix} M_8 = \begin{pmatrix} +1 & 0 & -1 \\ -2 & 0 & +2 \\ +1 & 0 & -1 \end{pmatrix}$$

$$M_9 = \begin{pmatrix} +1 & -2 & +1 \\ -2 & +4 & -2 \\ +1 & -2 & +1 \end{pmatrix}$$

These nine features are calculated on a sliding window from each of the component of C_s. Two statistical parameters are added to nine previous parameters:

$$\mu_v = \frac{1}{l} \sum_{i,j \epsilon v} A(i,j) \tag{1}$$

$$cov_v = \frac{1}{l^2} \sum_{i,j \epsilon v} (A(i,j) - \mu_v) \tag{2}$$

These two parameters (1) and (2) are calculated on the A intensities of the pixels (defined by i and j positions) on the squared neighborhood v with side l. The choice of the size window as $7 * 7$ results from preliminary tests [17].

Let E denote the space of candidates attributes. The number of attributes of E is $11*30 = 330$, where 11 represent the nine parameters of Laws filter and the two statistical parameters, and 30 is the number of colors components.

C. Mutual information

Mutual information (MI) is the measure of the dependence between random variables. The main difference with the correlation is that this last considers only linear relationships between variables. The MI of two discrete variables x and y is defined based on their joint probabilistic distribution $p(x, y)$ and the respective marginal probabilities $p(x)$ and $p(y)$:

$$MI(x,y) = \sum_{i,j} p(x_i, y_j) log \frac{p(x_i, y_j)}{p(x_i)p(y_j)} \tag{3}$$

The estimation of the joint probabilistic distribution $p(x, y)$ represents the principal difficulty for the use of MI. Various methods have been studied in the literature to estimate such joint distribution [14] (histograms and kernel-based methods). Authors in [8] propose a fast method to estimate the MI. One of the advantages of this method is that it based in the estimation of the entropy. The relation between MI and the entropy can be defined as [18]:

$$MI(x,y) = H(x) - H(y|x) \tag{4}$$

Using the properties of the entropy, the mutual information can be rewritten into:

$$MI(x,y) = H(x) + H(y) - H(x,y) \tag{5}$$

This entropy is calculated using k-nearest neighbor method [8].

This method has a second advantage. It allows the calculation between a set of features x and the output variable y. In the next section we will describe the algorithm for the construction of the hybrid color-texture space.

D. Hybrid color-texture space

In this part, an algorithm will select the attributes composing the hybrid color-texture space. These attributes are chosen from the space of candidates attributes E. The algorithm based on the mutual information is developed by [9]. It works in two steps. In the first step, the forward phase, attributes are adding one by one. At each iteration, the attribute selected to integrate the current subspace is the one that most increases the mutual information with the output variable. The forward phase is stopped when adding any new attribute decreases the mutual information. The second step is the backward phase. Attributes are eliminated one at time. The attribute that most increase the mutual information when it is discarded is eliminated from the subset of features. As in the forward step, the backward phase is stopped when discarding any other attributes decreases the mutual information of the subspace with the output variable. The final subspace is the hybrid color-texture space. It contains the attributes that are the most discriminate.

III. Vector machines classifier

Among the methods with kernels based on the statistical learning theory of Vladimir Vapnik, SVM are the most known.SVM is a method of binary classification by supervised learning, it was introduced by Vapnik in 1995 [15] [16]. This method is an alternative to the recent classification. This method relies on the existence of a linear classifier in an appropriate space. Since this is a problem of classification of two classes, this method uses a set of learning data to learn the parameters of the model. It is based on the use of so-called kernel function that allows an optimal separation of the data. It was successfully evaluated on pattern recognition problem [17] [18]. For example in two classes problem (positive and negative sets of simples), the basic form of linear SVM classifier try to find an optimal hyperplane that separates the set of positive samples from the set of negative samples. The $LIBSVM$ package that support multi-class problem available on [19] to classify the different textures is used in our work.

IV. Experimental results

In order to show the interest of our approach, the experiments were conducted on the $VisTex$ database, and on the $SPOT$ image of the region of $Rabat$ in $Morocco$.

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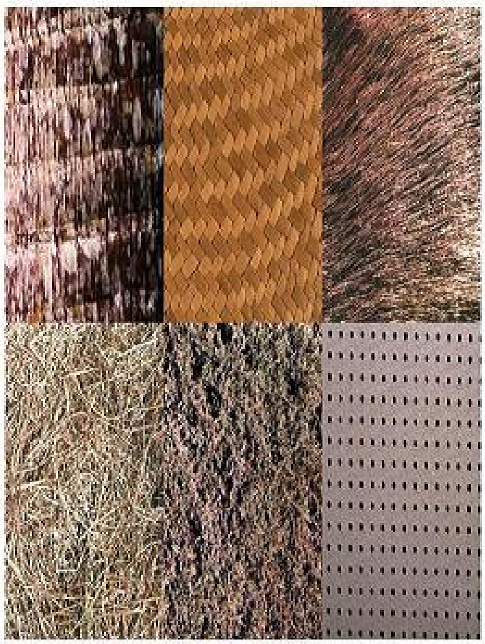

Fig. 1. Images of the VisTex database (left-right, up-down): Bark0, Fabric0, Fabric4, Grass1, Leaves12, Tile7

A. Vistex texture database

We randomly chose 6 textured color images of $512x512$ from the $Vistex$ database (Fig.1). Each image was divided into 64 non-overlapping sub-images of size $64x64$. The first 30 subimages of each texture were used for training, and the remaining 34 subimages were used for testing.

The table (I) and table (II) give respectively the result of the classification of each texture and the global accuracy of classification using SVM classifier. The result obtained in the hybrid color-texture space is better than the one in the RGB color space (89.5 Vs 85.3). Only 6 attributes are used for the classification of textures in the hybrid color-texture space instead of 33 attributes used in the RGB space.

TABLE I
VISTEX RESULTS(%)

Texture	RGB	hybrid color-texture space
Bark0	95.5	94.5
Fabric0	98.9	99.7
Fabric4	81	72.5
Leaves12	64.8	85.4
Grass1	85.8	89.5
Tile7	86	95.4

TABLE II
GLOBAL ACCURACY CLASSIFICATION (%) OF DIFFERENT COLOR SPACE

	RGB	hybrid color-texture space
Numbers of attributes	33	6
Global accuracy classification	85.3	89.5

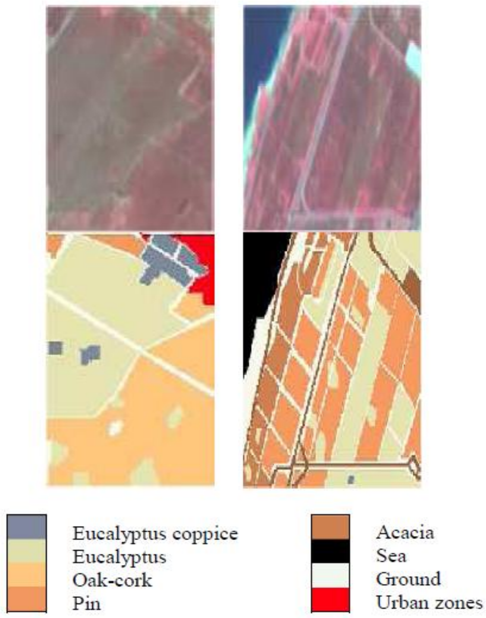

Fig. 2. The SPOT image

B. SPOT image

The SPOT image retained for this study was acquired in December 1999 with 20m of space resolution. In this image, two forest zones are concerned with respective size of 140x90 and 90x140 pixels occupied essentially by six classes of textures (Fig.2); five classes of forest: The eucalyptus coppice, the eucalyptus, the cork oak, the pine and the acacia. The sixth class corresponds to the sea. The three other classes (road, urban zones and ground) will not be classified because of their small number of points and their distribution on small pieces. So, the training cannot be done on these classes. The data base of parameters is divided into two parts: The training base and the test base. The training base is built on the following way: we extract manually, from the two test zones of image, six various textures corresponding to our classes. Then, we calculate, on a sliding window on these zones, the seven parameters of textures, five according to co-occurrence matrix and two statistical parameters. The training base was composed of 100 observations per class, that is to say, 600 on the whole classes. The test base is only composed of the points located in homogeneous zones.

The table (III) gives the number of samples per class in the test base. The table (IV) gives the result of classification obtained in the RGB color space. The result of classification in the hybrid color space using mutual information is given in table (V). Tables (III) and (IV) represent a confusion matrix of classification, where lines represent the true class and columns are representing class chosen by SVM. The global accuracy classification of different color spaces is given in the table (VI). This table shows that our approach provides better classification results than those obtained in RGB (53.2 Vs 68.3). Also our approach allows obtaining good results with a low number of features (33 Vs 5).

TABLE III
NUMBER OF SAMPLES PER CLASS IN THE TEST BASE

Texture(label)	Eucalyptus coppice (1)	Eucalyptus (2)	Oak-cork (3)	pin (4)	Acacia (5)	Sea (6)
Samples	92	3119	2464	394	85	252

TABLE IV
CLASSIFICATION RESULTS (%) IN RGB COLOR SPACE

	Eucalyptus coppice	Eucalyptus	Oak-cork	pin	Acacia	Sea
Eucalyptus coppice	33.3	2.7	6.6	57.4	0	0
Eucalyptus	28.4	62.6	2.6	0	6.4	0
Oak-cork	30.2	0.9	47.8	7.8	13.3	0
pin	3.9	19.6	22.3	9	45.2	0
Acacia	0	0	0	57.4	42.6	0
Sea	0	0	0	0	0	100

TABLE V
CLASSIFICATION RESULTS (%) IN THE HYBRID COLOR-TEXTURE SPACE

	Eucalyptus coppice	Eucalyptus	Oak-cork	pin	Acacia	Sea
Eucalyptus coppice	41.4	0	52	6.7	0	0
Eucalyptus	13.9	73	6.6	0	6.5	0
Oak-cork	26	0.8	72.7	0.5	0	0
pin	1.4	0.2	31.2	11.8	52.8	2.6
Acacia	0	0	0	72	28	0
Sea	0	0	0	0	0	100

TABLE VI
GLOBAL ACCURACY CLASSIFICATION (%) OF DIFFERENT COLOR SPACE

	RGB	hybrid color-texture space
Numbers of attributes	33	5
Global accuracy classification	53.2	68.3

V. CONCLUSION

In this paper we present the method of building a hybrid color-texture space using mutual information. A comparative study between our result and the one obtained in RGB color space shows that result obtained with our approach is promising. In future work, our approach will be generalized to other texture features as the contourlet transform and curvelet transform. We will also use other classifier as the neural network.

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