1D Moment Signatures for Random Colored Texture Characterization

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Abstract

In this article, we develop a new method of characterization of colored random textures. This method is based on the use of the chromaticity diagram combined with the 1D-geometric moments. In CIE XYZ color space, each pixel of an image is associated with a point within chromatic space, in which a color is characterized by its wavelength and its purity factor. Thus, we elaborate an attribute vector which includes color and gray-level characteristics. Color characteristics are computed by means of the moments of the purity factor histogram and of the wavelength histogram. The energy assigned to each pixel is taken into account by computing the moments of the gray-level histogram. In addition, the random nature of texture is taken into account by the variance of estimation error of a 2D-AR model. The relevance of this characterization has been evaluated by means of a classification process applied to 720 images of granite stones taken from the ‘‘marbleandgranite. com’’ database. We show that a attribute vector of dimension 7 makes it possible to reach a percentage of correct classification of 91%.

1. Introduction

Color and texture are two relevant attributes in image analysis. These attributes are in particular exploited when signatures are needed to efficiently classify and search textured images in a database of images. A number of methods exist to extract these color signatures. Among these, are the methods based on the modeling of histograms,[2,12] on wavelet correlation,[14] on co-occurrence matrices,[5,6] on color moments,[7,9,10] and others (Markov random field model,[8] color coherence vectors,[11] color correlograms[4]...).

In this article, we develop a new method of characterization of random color textures. This method is based both on the use of the chromaticity diagram and on the use of the monodimensional geometric moments.[3,13] It consists on elaborating an attribute vector which includes color and gray-level characteristics. In CIE XYZ space color, each pixel of an image is associated with a pair of values *(x,y)* within chromatic space, in which a color is characterized by its wavelength λ and its purity factor *p*. For a given image, we therefore establish the histogram of wavelengths as the histogram of purity factor. We determine the color signature of this image by means of the 1D-geometric moments computed on these two histograms. The choice of these moments is justified since they characterize efficiently either the position or the magnitude of the possible peaks of these histograms. Furthermore, their implementation is simpler than that required by gaussian mixture signatures.[2] The energy attached to each pixel is taken into account by extracting attributes on the gray-level image. These attributes are the variance of estimation error of a 2D-AR model and the first moments of the gray-level histogram. The choice of AR model is justified by the random nature of the treated images.[1] Experimental results of texture classification from an appropriate database[15] confirm the relevance of this method.

2. Theoretical Study

2.1 The Space Color Used

The CIE XYZ space is defined by the transformation of RGB space according to the relations:

$$\begin{aligned} X &= 0.607R + 0.174G + 0.200B \\ Y &= 0.299R + 0.587G + 0.114B \\ Z &= 0.066G + 1.111B \end{aligned} \tag{1}$$

and the chromaticity diagram *(x,y)* is deduced from (1) by defining:

$$x = \frac{X}{X+Y+Z} \qquad y = \frac{Y}{X+Y+Z} \tag{2}$$

From a given image, a set of points *(x,y)* is obtained, each point being characterized by its wavelength $\lambda(x,y)$ and its purity factor $p(x, y)$ (figure 1). In order to have a monodimensional problem, a system of polar coordinates (ρ, θ) is used, in which each point $M(x, y)$ is referenced in relation to the blue primary color (point B in figure 1). Thus, we have:

$$OM^2 = \rho^2 = (x - x_0)^2 + (y - y_0)^2 \tag{3}$$

For simplicity, the wavelength λ of a current point is measured by the angle $\theta = (\overrightarrow{OM}, \overrightarrow{OB})$. The colors actually used being located inside the triangle RGB (figure 1), we define the purity factor as

$$p = \frac{OM}{OA}.$$

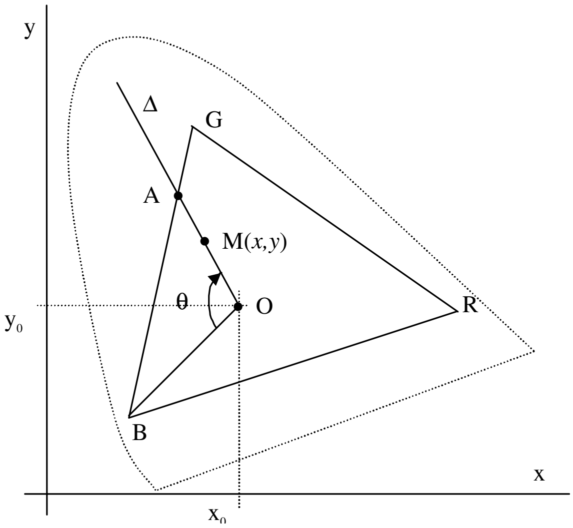


Figure 1. Representation of a point M in the chromaticity diagram (x,y).

2.2 One Dimensional Moments and Color Histograms

Let $f(x)$ be the probability density of the random variable X. The n^{th}-order statistical moments of $f(x)$ are expressed by the relation:

$$E(X^n) = \int_{-\infty}^{+\infty} x^n f(x)dx \tag{4}$$

In the general case where $f(x)$ is a continuous function of the variable x, the n^{th}-order moments of $f(x)$ are called ''geometric moments''[3,13] and can be written as follows:

$$M_n(f) = \int_{-\infty}^{+\infty} x^n f(x)dx \tag{5}$$

For practical purposes, the function $f(x)$ is digitalized and we call f_k the discrete values of $f(x)$. Then, the n^{th}-order moments of $f(x)$ are given by:

$$M_n(f) = \sum_{k=0}^{\infty} k^n f_k \qquad k \in N \tag{6}$$

Using the previous definitions and calling P the total number of points in the chromaticity diagram, we construct the histogram of the wavelength characteristic angles:

$$h(\theta) = \frac{1}{P}\sum_{i=0}^{P-1} \delta(\theta(i) - \theta) \tag{7}$$

Then, we compute the 1D moments of this histogram by taking the angles θ in the range [0, 360°] with a step of one degree. The 1D-n^{th} order moments corresponding to these histograms are defined by:

$$M_n(\theta) = \sum_{\theta=0}^{360°} \theta^n h(\theta) \tag{8}$$

The purity factor histogram is defined in the interval [0, 100], with a step equal to one.

$$h(p) = \frac{1}{P}\sum_{i=0}^{P-1} \delta(p(i) - p) \tag{9}$$

The corresponding 1D moments are given by:

$$M_n(p) = \sum_{p=0}^{100} p^n h(p) \tag{10}$$

With these definitions, the 0^{th}-order moments are all equal to 1 and will therefore not be taken into account.

2.3 Attribute Vector of Texture

In order to take into account color in the chromaticity diagram, a pre-treatment which allows us to keep pixels of high brightness is elaborated by means of a thresholding procedure. This operation makes it possible to generate an image I_1 each of whose points contains relevant colored information. On this image I_1, we calculate the K first moments of the wavelength histogram and the P first moments of the purity factor histogram.

The energy assigned to each pixel is not linked with the color attributes described above. This energy is taken into account by means of an attribute on the gray-level of the original image. This is done by computing the Q first moments of the gray-level histogram and the variance of estimation error of a 2D-AR model.

Let y_{kl} be the gray-levels of the studied image, b_{kl} the generating noise and c_{ij} the coefficients of the 2D-AR model. Thus we have the following relations:

$$y_{kl} - \sum_{(i,j)\in Mm} c_{ij} y_{k-i,l-j} = b_{kl} \qquad \sigma_b = \mathrm{var}\{b_{kl}\} \tag{11}$$

In summary, the attribute vector is made from four types of criteria:

- K moments of the purity factor histogram.
- P moments of the wavelength angle histogram.
- Q moments of the gray-level histogram.
- 1 coefficient resulting from 2D-AR modeling.

These types of criteria are respectively named ''purity factor'', ''wavelength'', ''gray-level'' and ''AR model''. The dimension of this vector is equal to K+P+Q+1.

3. Experimental Results

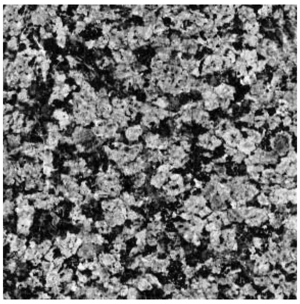
To evaluate the proposed method, minimum-distance classification is performed. The classification process is a simple comparison of the Mahalanobis distance between a candidate and the kernels of the training database.

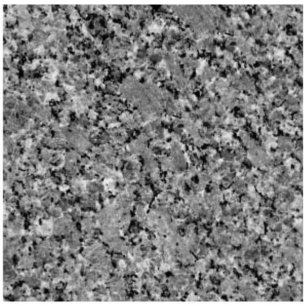
3.1 The Database

Experiments were carried out from a base of 80 colored textures taken from "marbleandgranite.com" database.[15] Each sample of size 288 x 288 pixels was cut into 9 sub-images of size 96 x 96 pixels, without any overlapping. The database is thus composed of 80 families, each with 9 samples, that is to say 720 textures in total. Figure 2 depicts two examples of textures used and also shows the corresponding histograms of the wavelength and of the purity factor.

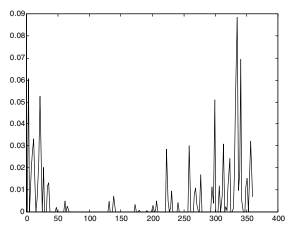
3.2 Recognition and Classification

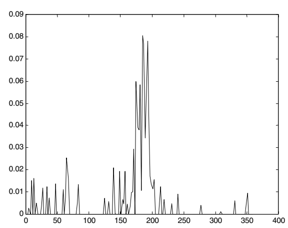
In order to characterize their performance according to the order of moments, we start with a classification process based on only one type of criterion. For the criterion called "AR model", the percentage of correct classification (PCC) obtained is 20.14%. For the three other criteria, called "purity factor", "wavelength" and "gray-level", table I summarizes the rate of correct classifications, with order of moments from 1 to 6.



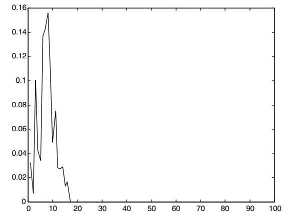


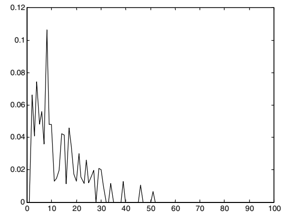
2a) Violetta *2b) Cariocagold*





2c) Wavelength histogram of violetta *2d) Wavelength histogram of cariocagold*





2e) Purity factor histogram of violetta *2f) Purity factor histogram of cariocagold*

Figure 2. The two textures ''Violetta'' (2a) and ''Cariocagold'' (2b). Wavelength histograms (2c-2d) and purity factor histograms (2e-2f) of these textures.

Table I. Percentage of Correct Classification, PCC in %, Versus Order of Moments.

Order of moments	1	2	3	4	5	6
Purity factor	18.9	34.0	37.5	38.3	38.5	38.6
Wavelength	24.7	45.1	49.3	51.4	52.2	52.6
Gray-level	22.5	33.2	36.8	39.2	41.8	41.8

In table I, it can be seen that the rate of success does not increase significantly when the order of moments exceeds 3. Moreover, the discrimination rates obtained from each criterion are rather close to each other, with, however, a predominance for the criterion "wave-length''. From this observation, we establish a procedure of recognition on the whole of the attribute vector components. This is done by choosing approximately the same order of moments on each criterion concerned. (K,P,Q)-moment combinations lead to an attribute vector of size K+P+Q+1. Table II gives some results as a function of the size of this vector.

Table II. Percentage of Correct Classification, PCC as a Function of Size of Attribute Vector.

Size of attribute vector K+P+Q	K,P,Q Combinations	Percentage of Correct Classification in %
5	(2,2,1)	89.3
6	(2,2,2)	91.0
	(2,3,1)	90.0
	(3,2,1)	88.5
7	(2,3,2)	90.7
8	(2,3,3)	90.7
9	(3,3,3)	89.6

For example, the combination (K,P,Q)=(2,2,2) leading to a vector of size 7, makes it possible to reach a rate of good classification of 91%. These values are quite satisfactory as compared to other methods.[10,14]

4. Conclusion

We have developed a new approach of characterization of random color textures. This method is based on the use of the chromaticity diagram combined with the 1D-geometric moments. An attribute vector has been elaborated with the moments of the histograms of the purity factor of the wavelength and of the gray-level. In addition, the random nature of texture is taken into account by the variance of estimation error of a 2D-AR model. The relevance of this characterization has been evaluated by means of a classification process applied to 720 images of granite stones. We have shown that a attribute vector of dimension 7 makes it possible to reach a percentage of correct classification of 91%. These results allow us to proceed in this way and to extend this method to more diversified textured images.

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Biography

Jacques Brochard graduated from the Faculté des Sciences of the University of Poitiers, France. He received a Ph.D. in Electronics from the University of Bordeaux, France, in 1970. From 1970 to 1984, he taught physics at college and since 1984 he has been with the University of Poitiers as an Assistant Professor of automatic control and electronics. His research interests in image processing include texture analysis and depth measurement.