Invariant Features for Colored Textured Surfaces Moving in a 3D Environment

Jacques Brochard, Majdi Khoudeir and Anis Ben Slimane
IRCOM-SIC, FRE-CNRS 2731, Cedex, France

Abstract

In this paper, we develop a new method for extracting invariant features for textured color surfaces moving in a 3D environment. This method is based on separation between chrominance which characterizes color of the surface, and intensity which characterizes the texture aspect. Invariant features for color are modeled by the first moments of the histograms of dominant wavelength and purity factor computed in the CIE-XYZ space. Invariant criterion for texture is computed by considering the evolution of the auto correlation function of gray-level images of surfaces in movement. Its value corresponds to the sum of the coefficients of the discrete correlation matrix. The relevance of this approach was tested on a synthetic database and also on real images of colored textured planes moving in the 3D-space. The three criteria which have been computed on these images appeared to be relevant and can be exploited to extract invariant signature.

1. Introduction

Color and texture are two relevant attributes allowing to extract image signatures. Numerous methods aiming to extract these signatures have been proposed in order to classify and search images in a database of images. Among these, are the methods based on the modeling of histograms,[9] on wavelet correlation,[10] on co-occurrence matrices,[4] on color moments.[6-8] Unfortunately, theses methods do not take into account the relative displacement between the camera and the studied surface. This displacement occurs when, for example, an image sequence is obtained by a camera with a changing shooting position with respect to the analyzed scene, or when a dynamic scene is being filmed from a fixed position. In order to avoid this drawback, different works have been achieved. Healey and Wang[5] developed a method for recognizing color texture independent of rotation, scale and illumination. Texture is modeled using Zernike moments of multispectral correlation functions. Funt and Finlayson[3] developed a method called color constant color indexing based on the coefficient model for sensor response that compares distributions of color ratios. Adjeroh and Lee[1] use the concept of color constancy to ensure invariance and then use some neighborhood considerations to introduce information about structure in the indices. However, in this case, one problem is the difficulty posed by highly textured images.

In this article we develop a new method to characterize colored textured surfaces moving in a three dimensional environment. This method is based on the two following points. First, the choice of a color representation space which do not depend on this type of movement, and second, the use of invariant criterion which characterizes the texture of the moving surface, independently of its color. For the first point, we choose the IHS space or a derived version and we characterize color by means of the moments of the histograms of Hue and Saturation components. For the second point we start with our previously work,[2] showing how to develop a method for invariant feature extraction on gray-level textured images undergoing affine transformation. This method is performed by transforming the autocorrelation function of the studied gray-level images followed by determination of an invariant criterion which is the sum of the coefficients of the discrete correlation matrix. In this paper, we consider that the sizes of the studied surface are always much smaller than the average distance between the object and the camera, so that we can use affine transformation. We present experimental results which confirm the relevance of this approach.

2. Theoretical Study

2.1. The Space Color Used

Representation of a color can be done in different 3-D spaces such as RGB, IHS, CIE-XYZ or CIE-Lab space and others. For our purpose, we have to choose a space which clearly distinguish hue and saturation components of a surface, whereas intensity will be separately treated. IHS and XYZ spaces are two good candidates and for computation commodity, we use the XYZ space in the following.

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 deal with 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). For simplicity, the wavelength λ of a current point is measured through 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

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

R, G, B points correspond to the three primary colors.

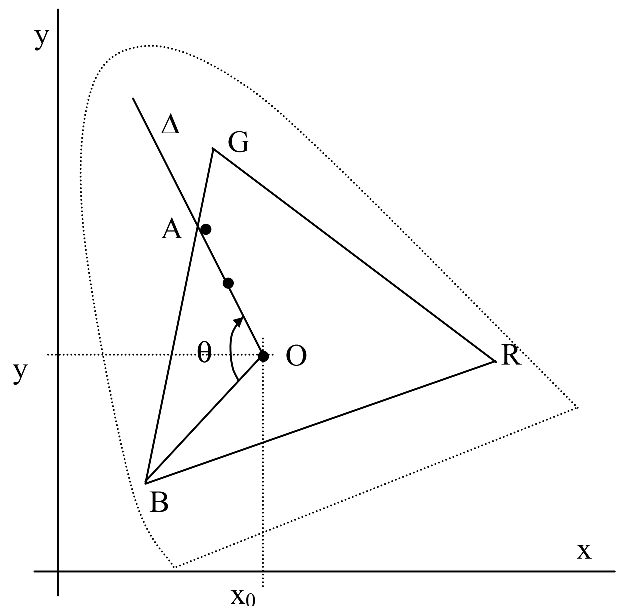

Figure 1. Representation of a point M in the chromaticity diagram (x,y)

Dominant wavelength λ, measured by angle θ, and purity factor p are then used to characterize color of the moving surface under study. For practical purposes, these values are digitized as θ_k and p_k, over a range of values $k \in [1,N]$.

2.2. Invariant Feature for Color

We make the hypothesis, physically realistic, that the dominant wavelength and the purity factor are very little affected by the relative movement between the surface and the camera. Then, we characterize these values by means of one-dimensional moments of their histograms $h(\theta_k)$ and $h(p_k)$ respectively. We compute the 1D moments of these histograms by taking the angles θ in the range [0, 360°] with a step of one degree and in the interval [0,100] for the purity factor, with a step equal to one. The 1D-nth order moments corresponding to these histograms are defined by:

$$M_n(\theta) = \sum_{\theta=0}^{360°} \theta^n h(\theta) \quad \text{and}$$

$$M_n(p) = \sum_{p=0}^{100} p^n h(p) \tag{3}$$

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

2.3. Invariant Feature for Gray Level Texture

In this section, we briefly recall our farmer results[2] on feature extraction of a textured plane moving in a 3-D space. It should be noted that colored images are firstly translated in gray-level images. The movement of the textured plane is broken down into a 3D rotation followed by a 3D translation. The different textured images obtained by a camera can be linked by an affine transformation **H** whose parameters depend on the orientation and the location of the 3D textured plane. To do this, the normalized autocorrelation function is viewed as a surface on which we consider a plane section (P) at a fixed height *h*. The plane section intersects the surface defined by ACF along an outline (*A*). We model this curve (*A*) by an ellipse which verify the classic equation in the *(x,y)* plane:

$$\alpha.x^2 + \beta.y^2 + \gamma.xy = 1 \tag{4}$$

Let *C* be the normalized autocorrelation function of a given texture. We summarize the different steps which allow us to make the correlations after affine transformations invariant as follows:

- Extract a plane section with height *h* from autocorrelation function *C*.
- Calculate the value of parameters α, β and γ of the corresponding elliptic outline.

- Obtain matrix $\mathbf{H}_{\mathbf{t}inv} = \begin{bmatrix} 1 & 0 \\ t_{inv} & 1 \end{bmatrix}$,

where $t_{inv} = -\frac{\gamma}{2\beta}$.

- Apply affine transformation $\mathbf{H}_{\mathbf{t}inv}$ to C to obtain autocorrelation function C_t.
- Extract a plane section with height *h* from C_t.
- Calculate the value of parameters α, β and γ of the corresponding elliptic outline.

- Obtain matrix $\mathbf{H}_{\mu inv\omega} = \frac{1}{\omega_{inv}} \begin{bmatrix} 1 & 0 \\ 0 & 1/\mu_{inv} \end{bmatrix}$,

where $\mu_{inv} = \sqrt{\frac{k_1\beta}{\alpha}}$ and $\omega_{inv} = \sqrt{\frac{\alpha}{k_2}}$.

- Apply affine transformation $\mathbf{H}_{\mu\omega inv}$ to C_t to obtain autocorrelation function $C_{t\mu\omega}$.
- Calculate the sum

$$S = \sum_{(i,j)\in D} r_{ij}$$

of the coefficients of the discrete correlation matrix $\overset{\Delta}{C}_{t\mu\omega}$.

D represents the part of the correlation matrix which includes a set of points around the central point.

Criterion S constitutes an invariant feature of images of a textured surface undergoing translations and 3D rotations.

Experimental Results

In order to test the validity of the proposed method, we carry out our experiments from two databases. The first one consists in four texture families which each contains 144 samples corresponding to different rotations and translations of an original textured surface.[11] These samples are computed from the four reference images as shown in figure 2. The second database is constituted by two families of eight images of real textured plane. Two colored planes are used, called "leopard-skin" and "fruits". These images have been taken with different distances and positions between the camera and the textured plane. Figure 3a and 3b show an example of representative samples.

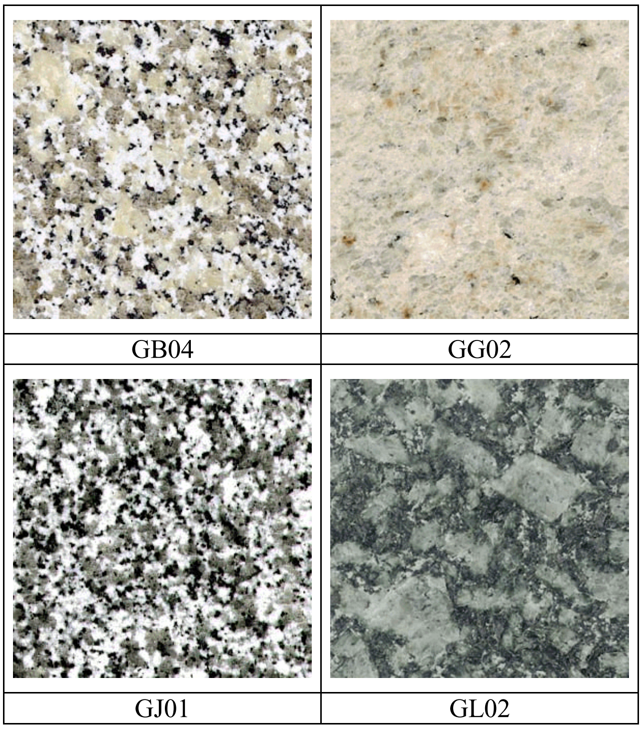

Figure 2. The four reference images of the synthetic database

For each sample of these two databases, we compute the criteria $M_n(\theta)$, $M_n(p)$ and S defined in sections 2.2 and 2.3. For clarity of presentation, only the three criteria $M_1(\theta)$, $M_1(p)$ and S are shown. Figure 4 shows the values of these criteria for the synthetic database whereas figure 5 regroups these values for the whole of real database.

An analysis of the figure 4 shows that, for the images studied here, these three criteria are good invariant features, with respect to the concerned transformation. This figure also shows a partial overlap of some value intervals of criteria $M_1(\theta)$ and S associated with each texture family. However, we can see that the association of the two criteria allows us to correctly discriminate the four texture families.

In the case of real images, figure 5 shows that the three criteria studied are also good invariants, especially $M_1(\theta)$ criterion, and allow us to obtain a correct discrimination of all the images of real database.

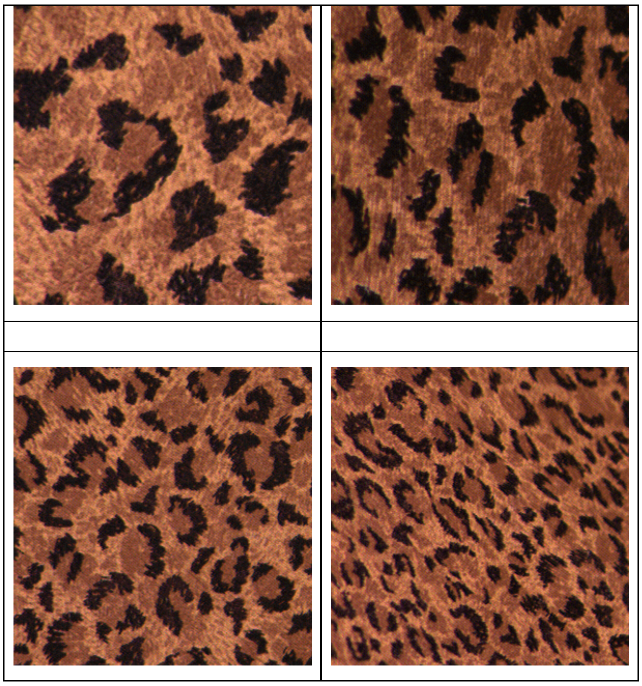

Figure 3a. Four samples of the real colored textured surface "leopard-skin" under different distances and rotations.

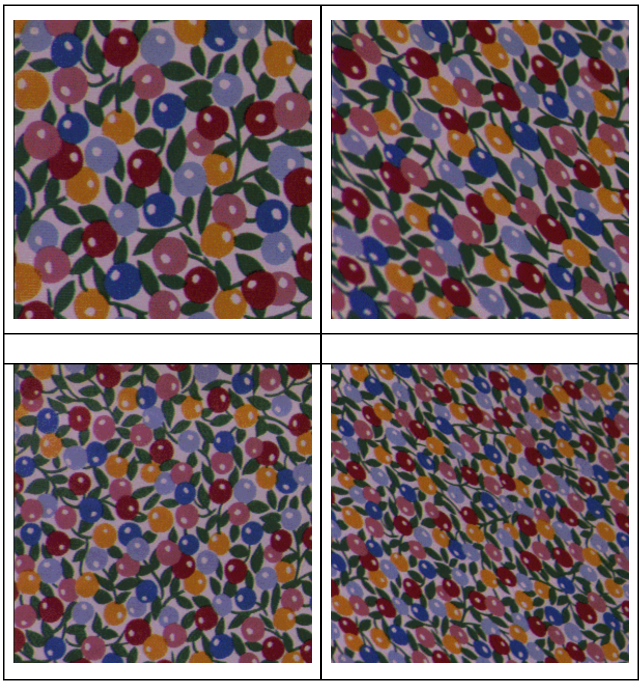

Figure 3b. Four samples of the real colored textured surface "fruits" under different distances and rotations.

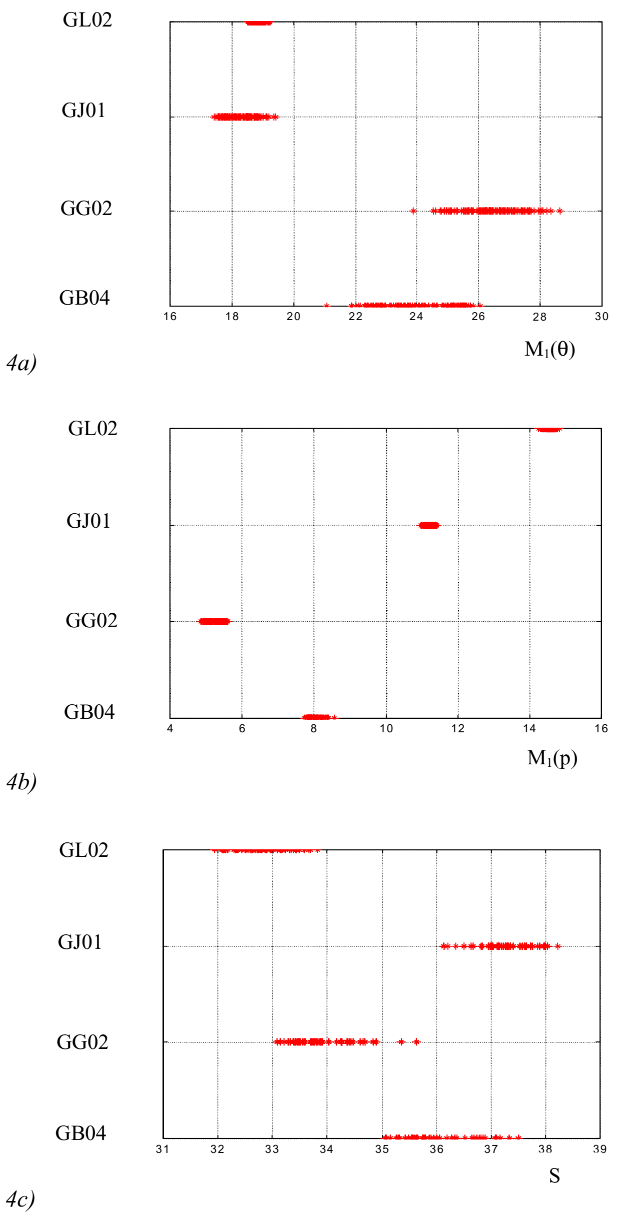

Figure 4. Graphical representation of criteria applied to four image family of synthetic database. 4a)- criterion $M_1(\theta)$, 4b)- criterion $M_1(p)$ 4c)- criterion S

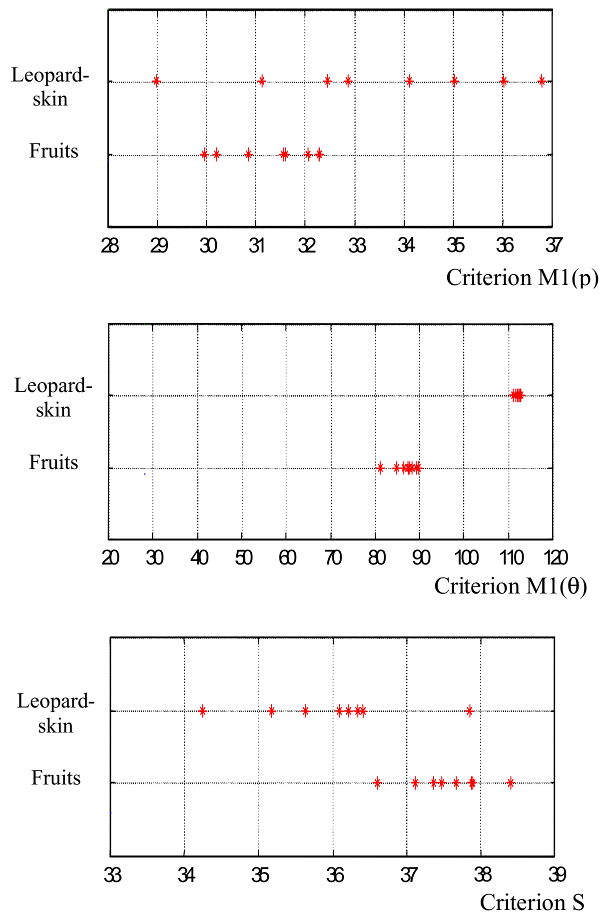

Figure 5. Graphical representation of criteria $M_1(p)$, $M_1(\theta)$ and S for the eight samples of the two families "leopard-skin" and "fruits"

Conclusion

We have presented a method to extract invariant features for colored textured surfaces moving in a 3-D space. This method is based on separation between chrominance which characterizes only color of the surface, and intensity which characterizes the texture aspect of studied surfaces. Invariant features for color are modeled by the first moments of the histograms of dominant wavelength and purity factor computed in the XYZ-space. Invariant criterion for texture is computed by considering the evolution of the autocorrelation function of images of surfaces in movement.

The relevance of this new approach was tested on a synthetic database of 576 samples and also on images of colored textured planes moving in the 3-D environment. The three criteria which have been computed on these images appeared to be relevant and can be exploit to extract invariant signature for image indexing.

References

1. D.A.Adjeroh and M.C.Lee, On Ratio-Based Color Indexing, IEEE Transactions on Image Processing, Vol.10, N°1, (2001).
2. J.Brochard, M.Khoudeir, B.Augereau, Invariant feature extraction for 3D texture analysis using the autocorrelation function, Pattern Recognition Letters, Vol.22, pp.759-768, (2001).
3. B.Funt and G.Finlayson, Color constant color indexing, IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 17, N°5, pg.522-528, (1995).
4. M.Hauta-Kasari, J.Parkkinen, T.Jaaskelainen, R.Lenz, generalized co-occurrence matrix for multispectral texture analysis, Proc. of the 13th Int. Conf. On Pattern recognition, pg.785-789, (1996).

5. G.Healey and L.Wang, Illumination-invariant recognition of texture in color images, Journal of the Optical Society of America, A, Vol.12, N°9, pg.1877-1883, (1995).
6. B.M.Mehtre, M.S.Kankanhalli, A.Nasrasimhalu and G.Man, Color matching for image retrieval, Pattern recognition Letters, Vol.16, pg.325-331, (1995).
7. G.Paschos, Chromatic correlation features for texture recognition, Pattern Recognition Letters, Vol.19, pg.643-650, (1998).
8. G.Paschos, Fast color texture recognition using chromaticity moments, Pattern Recognition Letters, Vol.21, pg.837-841, (2000).
9. M.J.Swain and D.H.Ballard, Color indexing, International Journal of Computer Vision, Vol.7, N°1, pg.11-32, (1991).
10. G.Van de Wouwer, P.Scheunders, S.Livens, D.Van Dyck, Wavelet correlation signatures for color texture characterization, Pattern Recognition, Vol. 32, pg. 443-451, (1999).
11. http://www.marbleandgranite.com

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 3D colored texture analysis and roughness surface study.