Influence of color spaces over texture characterization

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Abstract. Images are generally represented in the RGB color space. This is the model commonly used for most cameras and for displaying on computer screens. Nevertheless, the representation of color images using this color space has some important drawbacks for image analysis. For example, it is a non-uniform space, that is, measured color differences are not proportional to the human perception of such differences. On the other hand, HSI color space is closer to the human color perception and CIE Lab color space has been defined to be approximately uniform. In this work, the influence of the color space for color texture characterization is studied by comparing Lab, HSI, and RGB color spaces. Their effectiveness is analyzed regarding their influence over two different texture characterization methods: DFT features and co-occurrence matrices. The results have shown that involving color information into texture analysis improves the characterization significantly. Moreover, Lab and HSI color spaces outperform RGB.

Keywords: Texture analysis, Color Spaces, Discrete Fourier Transform, Co-occurrence Matrices.

1 Introduction

In the past years the few works that coped with color textures frequently did it by splitting the characterization process into two main steps: first, obtaining gray level texture features after changing the image into gray scale, and second, getting color features from the histogram of each color component [1]. Recently, some works have tried to face a global color texture characterization process [2]-[6].

Despite of being widely used, RGB space is not perceptually uniform in the sense that differences between colors do not match with human perception of color differences [7]. Color spaces such as Lab or HSI are less frequently used. Their main problem is their noise-sensitivity due to the non-linear transformations involved in the process of changing the space [8]. Even so, they have recently proved their effectiveness compared to RGB [9].

This work deals with the usage of different color spaces in the characterization of color textures and their influence over different texture characterization methods. Texture features will be extracted by means of two different methods and used to classify a limited database. We shall start considering features extracted from the Discrete Fourier Transform of the image. Leaving aside the frequency space, co-

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occurrence matrices [10] will next provide probability density information concerning the simultaneous occurrence of two values in the image at a certain relative position.

2 DFT features

As a discrete function, an image may be represented as a decomposition of Fourier components by the Discrete Fourier Transform (DFT). Besides, this transformation arranges the frequency space from lower to higher frequencies and regarding the direction these frequencies represent in the space domain. Thus, filters may be applied to select frequencies in bands (Fig. 1a) or with regard to their direction (Fig. 1b). In this way, we could split the whole Fourier space using ring or wedge filters and characterize the original image with the energy contained in each filter. However, in this way, directional information and band information are missed, respectively.

(a) (b) (c)

Fig. 1. (a) Ring filter, (b) Wedge filter of 45º (c) Tessels obtained with the product of rings and wedge filters

The product of a wedge by a ring provides with a small portion of the Fourier spectrum (Fig. 1c) which contains both directional and band information since it is located in a specific range of band frequencies and angles. A DFT tessellated in this way can also be characterized by the energies of these smaller parts (tessels). This should be a better characterization since it neither depends only on directional frequencies nor only on band frequencies but on both of them.

Gabor filters have already introduced similar techniques to obtain information of the different areas of the Fourier transform [11]-[14]. Nevertheless they require the usage of Gaussian filters which makes them computationally complex. Furthermore, as it is usual in the frequency domain, low frequencies are given more importance than medium and high frequencies as each frequency band is double the size of the previous one. In this way, low frequencies are thoroughly analyzed whereas medium and high frequencies lose significance. However, it has been proven that, in texture analysis, medium and high frequencies could be as important as low frequencies [16]. Therefore, a detailed analysis of all frequencies should be carried out to characterize textures. This is done by designing filters that keep the ring width constant from low to high frequencies, giving the same importance to all frequency bands. As we only intend to characterize the textures, energies of the tessels obtained in the product tessellation, will be used as texture features. Furthemore, they will require less computational effort when compared to Gabor filters.

2.1 DFT for color images

Color images have three gray scale components which all together give rise to color. A DFT generally deals with complex numbers but, when gray scale images are considered, the imaginary part is set to zero. In our proposal, the DFT of a color image will be a set of DFTs, each of them calculated from a pair of components in which the first one is the real part and the other one is the imaginary part. Therefore the color DFT will be composed by as many complex DFTs as combinations of two elements may be done with the components of the image. Unlike other methods that consider separately the luminance and the chromacity information, this approach could be easily extended to multispectral images just by considering all pairs of multispectral bands. As a color image has three components, there will be three combinations and so three complex DFTs will compose the color DFT of the original color image. Involving different components when calculating the DFT (complex planes) allows including color information in the characterization process.

As a different approach, color components may also be treated separately by calculating the color DFT simply as the composition of individual DFTs provided by each individual gray component.

3 Co-occurrence Matrices features

Let *G* be the number of gray levels in a gray image. A rotationally invariant co-occurrence matrix is a *GxG* matrix which contains the joint probability of pairs of pixels to appear at a fixed distance from each other, irrespective of the relative orientation the line that joins them forms with the reference direction of the image. In this case, a whole circle of pixels around a given pixel must be taken into account. When the orientation matters, so only one pixel could be separated a distance with certain orientation, the co-occurrence matrix is called directional [15][10]. There are certain statistical measures that portray a co-occurrence matrix which are used to characterize the texture where it was computed from. This is because they capture the relative abundance of certain image characteristics. Among the existing statistical measures energy, entropy, contrast and homogeneity have been used in this work for this purpose.

Images generally have 256 gray values (in the range 0…255) so their co-occurrence matrices are 256x256 sized. If a smaller matrix is wished in order to obtain more robust statistics, the number of gray levels may be reduced in the image obtaining, consequently, a smaller matrix. This could be done by means of equation (4).

$$g(i,j)_{new} = \frac{G-1}{255} * g(i,j)_{old} \tag{4}$$

where *G* stands for the new number of gray level.

In either case, the result is a co-occurrence matrix from which the statistical features may be computed in order to characterize the corresponding texture.

3.1 Cross-co-occurrence matrices

A co-occurrence matrix of a color image should keep representing a set of joint probabilities but now the computation will involve two components at each time to make the resulting set color representative. Now, when considering a pair of components, the joint probabilities are computed crossing components, that is, one pixel is considered in the first component and the second pixels is considered in the second component. So, once again, the number of co-occurrence matrices for an image is the combinations of the components taken in pairs.

No matter if the cross-co-occurrence matrix is rotationally invariant or directional, the change included ought to be the same. The methods applied regarding the distances between pixels remain.

Once again individual planes may be used instead of pairs of components, calculating the co-occurrence matrices of each component separately.

Lastly, the texture is portrayed by the statistical measures of the matrices calculated from its components, either using pairs of components, which we will call *complex planes*, or individual planes.

4 Color spaces

Images are originally represented in *RGB* color space. In this model, each color is represented as three values *R*,*G* and *B* which indicate the amounts of red, green and blue that make up the color. Nevertheless, other spaces should be taken into account as they may be convenient for texture characterization because of being perceptually uniform and/or closer to human color perception [7].

HSI (hue, saturation, and intensity) is an alternative color space. This is a more intuitive method of describing colors and, because the intensity is independent of the color information, it is a very useful model for image processing [9].

The International Commission on Illumination (CIE) defined three standard primaries (*X*, *Y*, and *Z*) to replace red, green, and blue, because all visible colors could not be specified with positive values of red, green and blue components. However, *XYZ* is not perceptually uniform. Perceptually uniform means that a change of the same amount in a color value should produce a change of about the same visual importance [7].

Lab space is derived from the *master* color space *CIE XYZ*. The intention of *Lab* color space is to create a space which can be computed from the *XYZ* space, but being perceptually uniform. *Lab* color space is a color-opponent space with dimension *L* for lightness and *a* and *b* for the color-opponent dimensions [7]. Therefore this color space represent the chromaticity with components *a* and *b* and the lightness *L* separately.

This division into chromaticity and lightness makes possible to study the impact of the lightness in the characterization. Chromaticity components may be treated as previously explained (creating complex planes) whereas *L* primary may be treated separately as an independent component (individual plane).

4 Experimental setup

Textures will be characterized using different methods. First, we use a tessellation of its color DFT so textures will have as many features as tessellated parts exists within their set of DFTs. The features that will portray textures in order to distinguish one another are the mean energies computed from the tessellated parts of the color DFT of the texture.

A study of the impact of the parameters used over the final classification rate obtained has been done over several texture databases. Performance increases when the size of the wedges used increases progressively from 5º to 45º and decreases afterwards. No increase or decrease of a 4 frequencies ring width obtains a gain. Therefore, experiments have been performed with a ring width of 4 frequencies and an angle of 45º for wedges. The particular parameters may depend on the properties of the images taken into account, but the chosen parameters performed well over a wide range of texture databases.

The second and third texture characterization methods will be based on the rotationally invariant and directional cross-co-occurrence matrices, respectively. Regarding the rotationally invariant mode of creating a co-occurrence matrix, we have used four different distances for each image so four different matrices result with their four features each (energy, entropy, contrast and homogeneity). Turning to the directional ones, four different directions have been involved by using four fixed movements: (x=1,y=0) for representing the 0º direction, (x=1,y=1) 45º direction, (x=0,y=1) 90º and (x=-1,y=1) for 135º. Besides, within every direction the value of the distance changes four times starting from two and adding two units each time. Briefly, for each sample one co-occurrence matrix and its features are calculated for each distance belonging to the four directions, that is, 16 matrices are computed each time.

The characterization taking into account several components can be performed by complex planes which are a combination of the components giving rise to a complex pair or by individual ones, which make no combination among them.

The database used to test the quality of the characterization by classifying textures is shown in Fig. 2 which is originally a twenty-four 512x512 sized color image database. Images have also been converted to gray scale for gray characterization purposes. This database comes from the well-known VisTex bigger database [17].

Each texture will represent a class. The incoming image will be equally divided into 64 samples, each one with 64x64 pixels size. Every sample obtained will be subjected to the same process, giving rise to features of a certain class. Consequently, there will be as many samples as parts the image is divided into.

For building the classifier, samples belonging to the same class are split into training and test sets, 25% and 75% of the samples, respectively. The division within the same class is made at random among the samples obtained in the computation of features. Classifier built for this purpose has used the k-nearest-neighbours (knn) rule with $k=3$. The test samples are used with the classifier and a classification rate is obtained. The whole process is repeated one hundred times and the mean of the error rates of these attempts is taken as the final performance of the classifier.

Fig. 2. Images which composed the texture database scaled down for displaying purposes (originally 512x512 pixels).

5 Experimental results

Each method used to characterize an image result in a different set of textural features. For the sake of validating these characterizations the classifier is used over the features obtained. The better a characterization portrays textures the higher rate of classification is obtained, as characteristics of samples belonging to the same class will be similar enough to make the classifier match samples with their class.

To evaluate all methods described, a brief summary of their performance is presented in Table 1. Characterization has been checked for each color space. The advantage of using color images can be also observed comparing gray level characterization which is included as well.

Table 1. Classification rates (in percentage) with characterization using DFT features, rotationally invariant and directional co-occurrence matrices features in different color spaces with 64x64 pixels sized samples using KNN classifier (K=3).

Image model		DFT characterization	Rotationally Invariant Co-occurrence	Directional Co-occurrence
Gray level		69.96	64.02	74.07
RGB	Complex planes	85.30	80.52	85.10
	Individual planes	86.52	77.59	83.25
HSI	Complex planes	88.30	89.67	90.54
	Individual planes	83.57	87.49	90.01
LAB	Complex planes	91.85	89.14	89.01
	Individual planes	92.23	87.49	90.43

From Table 1 we can note that no matter the characterization method considered, the introduction of color information in any color space improves significantly the characterization of the textures and consequently the classification rates of the samples in the database, as it could be expected.

Turning to color spaces, we can notice that *RGB* is not an adequate color space for characterizing textures. Any alternative color space tested outperforms its classification rates, no matter the characterization method used. While co-occurrence matrices methods perform similarly under either *HSI* or *Lab* spaces, DFT features method enhance significantly under *Lab* color space, supplying the highest classification rates.

In general, complex planes provide a better characterization of the texture than individual planes, but the differences are not as important as expected. In fact, in several cases, the classification rates obtained using individual planes are a little bit better than using complex planes. These small differences between complex planes and individual planes may be due to the high correlation of the information that appear in the different color planes. Perhaps some sort of data transformation, like PCA, may improve the characterization using complex planes

6 Conclusions

Analysis of textures has been tackled going through gray level textures and *RGB* color textures. To analyze the incidence of the color space over the characterization process several characterization methods have been tested. A decomposition of the DFT keeps involving color information in the features provided and is computationally inexpensive, though. On the other hand, well-known co-occurrence matrices have also been used.

As it was expected, the increase of components provides a better characterization of the textures and, consequently, better classification rates, so it seems that the use of color images is always convenient in the search of a better characterization.

Different color spaces were used to deal with different texture characterization methods. Results show the better performance of the approximately uniform color spaces over the traditional *RGB* space (not perceptually uniform) no matter the characterization method used. Thus, the evidence presented in this paper suggests that approximately uniform spaces could be superior spaces compared to non-uniform ones.

We still have to analyze if any data transformation could lead to an improvement of the results provided using complex planes when compared to the results obtained using individual planes. Also, the influence of the classifier used will be taken into account.

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