Color Texture Recognition and Indexing by Fuzzy Color Spatial Distributions

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ABSTRACT

This paper proposes two color texture descriptors based on the introduction of a fuzzy color symilarity function: the spatial color similarity pattern and the spatial color symmetry spread index. Both descriptors embed information on the spatial color distribution within a first-order statistical distribution. Experiments show that the proposed descriptors can be successfully used for color texture recognition and retrieval.

1 INTRODUCTION

All image processing algorithms must deal with the imprecision and vagueness that naturally arise in the digital representation of visual information. Noise, quantization and sampling errors, the tolerance of the human visual system are the cause of this imprecision. This strongly suggests that fuzzy models may be used for taking them into account.

The description of color textures emerged as a real challenge, especially after the massive interest shown in recent years for image retrieval and indexing systems [12], [9]. Indeed, generalist color images can be effectively described following a color–texture–feature paradigm [3], [9]. Color alone, although was proven to be the main human perceptual factor [8], cannot provide enough discriminative power between images. Color texture and strong visual features (such as edges or corners) must be taken into account. Still, many problems arise in the definition of color texture parameters and in color edge extraction, due to the vector nature of color data, which implies the necessity of developing new processing and analysis methods. Thus, we will investigate the possibility of obtaining texture descriptors that embed spatial information about the color distribution by using fuzzy color models and fuzzy color similarity measures.

The remainder of the paper is organized as follows: section 2 presents some fundamentals of fuzzy color modeling, section 3 introduces the proposed fuzzy-based texture descriptors, and section 4 presents some experimental results. Finally, section 5 presents some conclusions.

2 FUZZY COLOR MODELS

In the case of color images, color attributes and color differences play a particularly important role in the perception of objects. The process of measuring color differences must be designed to maintain a balance between the computed and the perceived difference. The CIE (*Commission Internationale d'Eclairage*) regulations specify color spaces (the Lab family) that provide a perceptual color difference equal to the Euclidean inter-vector distance. Still, the simple use of that color representation does not explain the similar perception and the visual confusion of certain colors. We propose to deal with this factors in the framework of a fuzzy color representation.

We will thus associate to each color $\mathbf{c}$, that usually is a point in the three-dimensional color gamut $\mathbf{C}$ (determined by the color space representation), a Lukasiewicz function, $\mu_{\mathbf{c}} : \mathbf{C} \rightarrow [0,1]$ that measures the membership degree of any color $\mathbf{c'}$ from $\mathbf{C}$ within the class "color $\mathbf{c}$". Thus, $\mu_{\mathbf{c}}(\mathbf{c}')$ is a scalar within [0,1] that expresses how similar is the color $\mathbf{c'}$ with respect to the color $\mathbf{c}$.

The analytical definition of the function $\mu_{\mathbf{c}}$ must take into account the natural perception and thus $\mu_{\mathbf{c}}$ must be decreasing with respect to the inter-color distance $d(\mathbf{c},\mathbf{c'})$ (regardless the definition of that distance). A typical model is the one proposed by Haffner [5] (in the framework of comparison of color histograms for image indexing):

$$\mu_{\mathbf{c}}(\mathbf{c}') = \exp\left(-\sigma\left(\frac{d(\mathbf{c},\mathbf{c}')}{d_{\max}}\right)^2\right), \qquad (1)$$

with

$$d_{\max} = \max_{\mathbf{c},\mathbf{c}'\in\mathbf{C}}\left(d(\mathbf{c},\mathbf{c}')\right). \qquad (2)$$

The tuning parameter σ in (1) allows to consider color similarity functions that are more or less localized, and thus to modify the inter-color confusion. We may also notice that the expression in (1) implicitly depends on the maximal dimension of the color gamut (through $d_{\max}$) and thus takes into account the color quantization. Once the color quantization is chosen and thus

$d_{\max}$ is determined, the tuning parameter σ can be easily related to the imposed similarity degree μ_1 associated to a color lying at an unitary distance ($d(\mathbf{c}, \mathbf{c}') = 1$) from the target color $\mathbf{c}$, by $\sigma = -d^2_{\max} \ln \mu_1$. A similar model (but oriented for the processing within the Lab color space) was proposed by Vertan et al [13] as:

$$\mu_{\mathbf{c}}(\mathbf{c}') = \begin{cases} 1, \text{ if } d(\mathbf{c}, \mathbf{c}') \leq JND \\ \max\left(0, 1 - \frac{d(\mathbf{c},\mathbf{c}')}{\sigma JND}\right), \text{ if } d(\mathbf{c}, \mathbf{c}') > JND \end{cases} . \tag{3}$$

In the equation above, JND is the just noticeable color difference, which, for the Lab color space, equals 2.3. We will further prefer the form from (1), as it is smoother and color space independent.

3 FUZZY LOCAL DISTRIBUTION MEASURES

3.1 The spatial color similarity pattern

Ojala [10] first introduced the concept of local binary pattern (LBP) for the description of texture. A LBP is defined for a given pixel within a gray-level image as the weighted sum of the thresholded values (according to the value of the current processed pixel) within the 3 x 3 neighborhood of the processed pixel. Thus, a binary pattern is associated to the processed pixel. The weighting mask implements a binary-to-decimal coding of the binary pattern, as shown in figure 1. Based on

1	2	3
4	5	6
7	8	9

0	0	0
0	1	1
1	1	1

1	2	4
128	0	8
64	32	16

Neighborhood LBP Mask

Pattern=00011110

LBP=8+16+32+64=120

Figure 1: The computation of a LBP (according to [6, 7]).

the same technique, several extensions have been defined [6, 7], in order to introduce the multiresolution approach [7] and the transitional and symmetry coding of the binary pattern [6].

However, the simple principle of thresholding cannot be applied to color (or, generally, to any vector-valued) images, since a direct, simple and topolgy-preserving ordering relation does not exist within a vector space [1]. We propose to replace the binary ordering relation between two colors with the fuzzy similarity degree between the two colors, computed according to (1). The thresholding operation is thus replaced by the computation of the similarity between the color of the current processed pixel and the colors of its eight neighboring pixels. The result of this operation is real-valued, and it is incorrect to called it LBP. Still, we will maintain the principle of computing a single scalar that embeds the pattern, by using the same weighting mask as in figure 1. The obtained scalar will provide the same $[0, 256]$ range as the basic LBP (see figure 2).

1	2	3
4	5	6
7	8	9

0	0.25	0.5
0.75	1	0.75
0.5	0.25	0

Neighborhood Similarity

Pattern=0 0.25 0.50 0.75 0 0.25 0.5 0.75

index=2/4+4/2+883/4+32/4+64/2+128*3/4=144.5

Figure 2: The computation of the spatial color similarity pattern; the similarity between the values i and j within the image region is modeled by $\max(0, 1 - |i - j|/4)$.

3.2 The spatial color symmetry spread index

The spatial color symmetry spread index is a scalar that can globally characterize the second order statistical distribution of pixels having a same color within a spatial neighborhood. Thus, this index will enable the distinction between edge pixels, corner pixels and coherent pixels (placed in uniform color regions). For each image pixel we consider a squared, centered neighborhood. Within this neighborhood, all pixels having the same color as the color of the central pixel are marked as ones, all other pixels being marked as null. For the resulting binary mask we compute the number of one-valued pixels within several symmetrical distributed mask slices. We will use an eight slides partitioning of the mask ($Q_1 - Q_8$, as shown in figure 3, in order to favor the rotation invariance. We may note that all the slices of the mask contain its central pixel. Let we denote by s_i

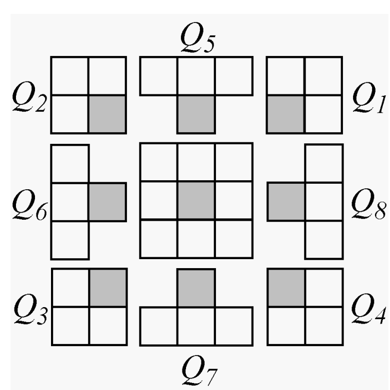

Figure 3: A 3 x 3 mask partitioned into eight partially superposed slices.

the sum of values within each mask slice Q_i. If all the s_i

numbers are about the same, it means that the central pixel belongs to an area of relative symmetrical spatial distribution of its color. If there are dissimilarities between the s_i numbers, the central pixel is characterized by a color that is unevenly distributed in its neighborhood. We define the color symmetry spread index S as (4):

$$S = \frac{\max_i\{s_i\} - \min_i\{s_i\}}{\sum_i s_i}. \quad (4)$$

It can be easily noticed that the S index is a range-to-mean ratio and measures the uniformity of the set $\{s_i\}$.

4 EXPERIMENTS

The main test database (`Ornament`) consists of 140 classes of colored ornamental stones (marble, granite, travertine and limestone), taken from the web site of Marble and Granite, Inc. (`http://www.marbleandgranite.com`). From each original image we randomly cropped ten 128 by 128 sub-images, that form its corresponding class, for a total of 1400 images. We equally used the generalist color texture database (`Textures`), consisting of 100 classes of nine 128 by 128 images of various natural and artificial, regular and irregular textures, for a total of 900 images (part of this database is taken from the well-known MIT Vistex texture database `http://www.media.mit.edu/vismod`; see figure 4 for a preview of a random selection of typical natural texture images within the `Textures` image database).

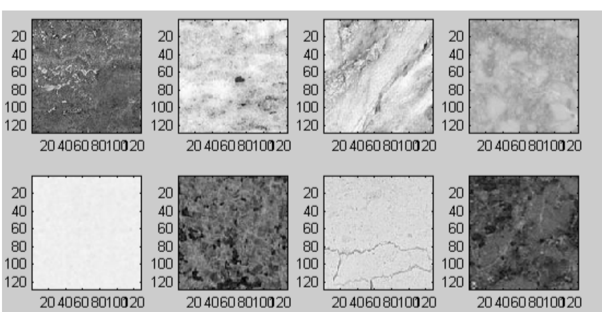

Figure 4: Typical textures within the `Ornament` image database.

Each color texture is described by the histogram of spatial color similarity patterns and the average (w.r. to the entire image) spatial color symmetry spread index. Both measures are computed for a six-bin uniform quantization of each RGB color component (yielding thus a 216 fixed color quantization) and $\mu_1 = 0.25$. The recognition performance is measured by the average recognition ratio (for all images within the database) according to a 1-, 3-, 5- and 7- nearest neighbor (NN) technique.
Since the correct class membership is known for any image within the database, we evaluate the quantitative, objective retrieval performance of the proposed descriptors by the classical precision-recall curves [3]. The precision is the percent of correctly retrieved images within the total number of retrieved images. The recall is the percent of correctly retrieved images with respect to the total number of relevant images within the database. The precision-recall curve plots the precision for all the recall rates that can be obtained according to the current image class population (C=9 for the `Textures` image database and C=10 for the `Ornament` image database), from 1/C to 1, in steps of 1/C. As shown in figures 5 and 6, the proposed description scheme provides superior indexing performance.

Texture parameters	Recognition rate [%]			
	1-NN	3-NN	5-NN	7-NN
RGB histogram	79.11	64.33	50.89	38.33
RGB histogram & Forier disks	78.56	66.89	56.78	46.67
RGB histogram & Galloway & Dasarathy	81.67	67.56	55.33	44.78
Proposed fuzzy index histogram	92.89	88.33	83.33	77.56

Table 1: Recognition rates for the generalist texture image database `Textures` based on a k-Nearest Neighbor algorithm (with k=1,3,5,7). The classical Fourier energy distribution within concentrical disks [11] and the Galloway [4] and Dasarathy [2] run-length matrix parameters are computed for the texture description.

Texture parameters	Recognition rate [%]			
	1-NN	3-NN	5-NN	7-NN
RGB histogram	87.93	76.79	69.43	59.64
RGB histogram & Forier disks	81.64	72.07	63.21	55.64
RGB histogram & Galloway & Dasarathy	90.79	80.71	72.64	62.71
Proposed fuzzy index histogram	96.00	94.50	92.43	91.07

Table 2: Recognition rates for the generalist texture image database `Ornament` based on a k-Nearest Neighbor algorithm (with k=1,3,5,7). The classical Fourier energy distribution within concentrical disks [11] and the Galloway [4] and Dasarathy [2] run-length matrix parameters are computed for the texture description.

5 CONCLUSIONS

The proposed approach is more effective in both recognition and retrieval performance than classical descriptors that combine separate color description (by color histogram or average color) and texture description (by spectral energy distribution or run-length matrix based parameters). The fuzzy approach to color similarity and color modeling provides the means to consider both color rankings and comparisons and the possible use of

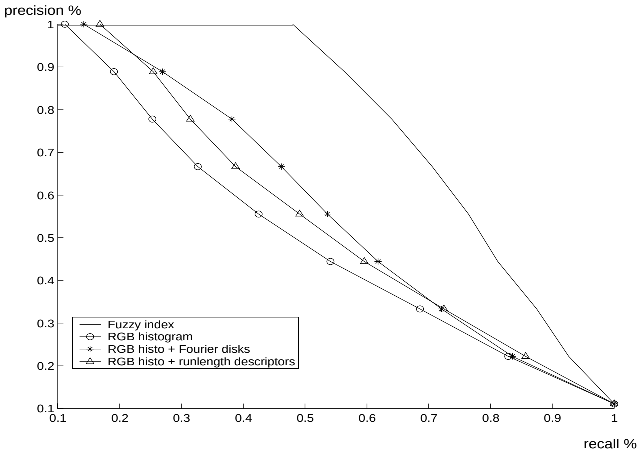

Figure 5: Precision-recall curves for the `Textures` image database: proposed fuzzy description (upper continous curve), RGB color histogram (circle-marked curve), RGB color histogram and Fourier energy distribution [11] (star-marked curve) and RGB color histogram and runlenght parameters [4, 2] (triangle-marked curve).

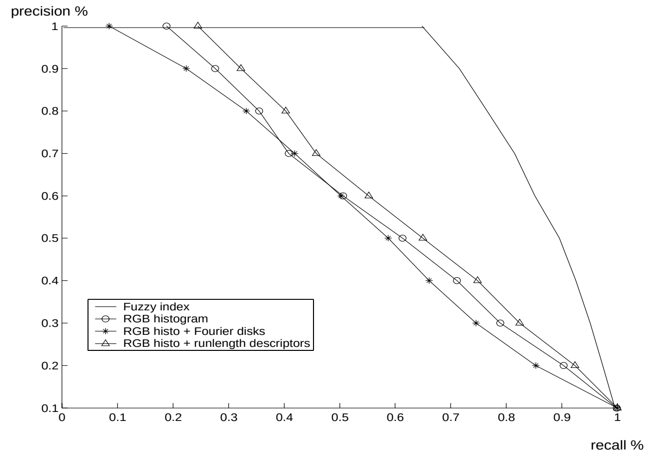

Figure 6: Precision-recall curves for the `Ornament` image database: proposed fuzzy description (upper continous curve), RGB color histogram (circle-marked curve), RGB color histogram and Fourier energy distribution [11] (star-marked curve) and RGB color histogram and runlenght parameters [4, 2] (triangle-marked curve).

a multiresolution representation (as the color similarity function becomes wider, the overal effect is to consider the image at a lower resolution). The fuzzy multiresolution approach will be further investigated.

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