IRIS – Color Texture Indexing and Recognition Toolbox

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Abstract - This paper presents an open-system approach to color texture recognition and retrieval. Several new compact texture descriptors are used in order to achieve a good recognition and retrieval performance. The IRIS system is an easy-to-use, user-friendly Matlab toolbox, which allows the user to browse image databases according to different paradigms.

Indexing terms - color texture description, color image retrieval, ornamental stones description, retrieval toolbox

I. INTRODUCTION

The growing demand for fast and accurate access and information retrieval has extended to visual information as well. The multimedia revolution of the last years imposed ever more demanding image handling requirements, in displaying, storing, searching and analyzing visual information. The Internet and the World Wide Web are certainly part of this evolution. The recent emphasis on image retrieval systems, by visual and content similarity, strongly illustrates the need for the development of effective image description schemes. In the context of retrieval, the descriptor is used to search in a database for images that are similar to the given image. Image description involves extracting relevant features from images within the database, such that a mathematically computed distance between feature vectors corresponds to the visual distance (or visual similarity) between the images. The main goal of an image description scheme is to provide a compact feature vector, embedding most of the visual cues characterizing the image: color, texture, and structure.

The remainder of the paper is organized as follows: section II presents the basic principles of the image content description for indexing systems, section III presents the new color texture descriptors used by the IRIS system and section IV briefly presents the structure of the IRIS system. The description of color texture recognition and indexing experiments (section V) and some concluding remarks (section VI) end the paper.

II. COLOR AND TEXTURE DESCRIPTION FOR IMAGE RETRIEVAL

Most of the generalist content-based image retrieval systems consider the color image description according to a color-texture-shape scheme. The color attributes (color moments, color distributions, color saturation, color balance) reflect the overall perception of the image, which, according to a recent study by Mojsilovic et al [9], [8] is the most important human classification criterion. The texture description, which still does not have a rigorous definition, translates linguistic terms, such as coarseness, roughness, regularity, directionality, and contrast. The shape description reveals either the global distribution of structural features (such as edge strength and orientation, corners and other shape primitives), either specific shape descriptors, following a segmentation or region-of-interest identification procedure. We consider that shape information can be partially covered by a proper texture description and partially reflects very specific domain-oriented knowledge.

A. Color description

Beginning with the works of Swain and Ballard [16], the first order statistical distribution of colors (color histogram) became the most intensively used tool for image content characterization. The alternative use of the associated cumulative distribution function [14] proved to perform better with respect to small color variations. Even simpler and more compact, the statistical moment description of the image content summarizes the image description by a few, marginal central moments (dispersion, kurtosis, mean) either of the color distribution, as proposed in [14], [9], or of the chromaticity distribution [11]. Other works [1] are based on the compression of the color (or chromaticity) distribution by a partial (via the cosine transform) or total decorrelation (via the principal component analysis). Still, it appeared very early that the first-order distributions and their associated moments have some intrinsic limitations, since they cannot account any spatial information about the colors (see for instance the basic examples presented in [5]). The use of color description techniques implies the prior choice of a color space representation and of a color quantization procedure [2].

The color space representation is chosen according to one of the three usual color paradigms:

- RGB or luminance and two differential chromatic components (linearly transformed RGB, which includes the biologically motivated opponent color representation and the PCA-based representation of Ohta),
- the uniform chromaticity color space Lab or Luv (which provides an inter-color distance that matches the visual perception), and

- the perceptual representation (hue, saturation, value) HSV and its many variants (as presented for instance in [2]).

The color quantization can be fixed (some basic colors that "are never confused"), uniform (each color component being independently uniform quantized, not necessarily with the same number of quantization levels) or adaptive (images with color tables).

B. Basic texture description

Texture still lacks a specific, rigorous definition. It can be described either as a mostly regular spatial replication of a basis pattern (the "texon" or "texel"), or as an irregular, or random distribution of pixel values. According to the chosen model (deterministic or stochastic), the texture attributes derive from the computation of characteristic visual cues (periodicity, orientation, principal axes, symmetry axes) or from the probability density functions of the pixel values, or spectral energies (or many other statistical based models).

The most commonly used spatial measure for texture discrimination is the co-occurrence matrix, which describes spatial relationships between gray levels in a texture. Some texture features, such as energy, entropy, contrast, homogeneity, tendency to clustering can be computed starting from the co-occurrence matrix, as proposed by Haralick [4]. Similar textural measures, such as contrast, coarseness and directionality, were used for texture discrimination in the QBIC system [10].

Another idea is to compute the power spectrum of the texture image, by a Fourier transform. Energies within different sub-masks (concentrical, diadically-spaced disks, or circular sectors) form a vector based on which textures are discriminated. Other possible approach is to compute a so called "texture signature"; Randen and Husoy [13] proposed to compute several "energy images" by convoluting the textured image with different filtering kernels. Thus, a pixel is characterized by a vector, which represents the textural neighborhood energies. Another idea is to determine a stochastic model that could be used to generate a given texture. Then, the texture similarity is assessed by comparing the parameters of the corresponding models (2-D auto-regressive processes or Markov random fields).

C. Feature and shape description

Important visual cues, such as corners and contours can be taken into account, either explicitly, or implicitly. Edge orientation distributions, edge strength distributions and edge length distributions are used in conjunction with color descriptors for a robust retrieval performance in generalist image databases, as presented in [2]. Edge strength is used implicitly in the so-called histogram refinement techniques, such as the Color Coherence Vectors (CCV), introduced by Pass and Zabih [12]. A coherent pixel is defined by the color uniformity of its neighborhood, whereas the contour pixel is located close to the separation lines between the image objects and thus it is characterized by a non-uniform neighborhood. The CCV is thus a separate counting of contour and coherent pixels, into two color distributions (histograms).

Finding significant image parts is an ill-posed problem and relates to image segmentation. Image partitioning can provide the advantage of a refined query, but, usually, this implies a computational overload. Using the entire image as a query region is the simplest approach. Shape parameters are not very relevant since they can express only the aspect ratio of the pixel matrix. A somehow improved approach is to consider an image pyramid - the entire image at various resolutions (constructed by Gaussian or wavelet smoothing) - as a means to integrate the distance-related visual perception effects. Since most of the visual information perceived by the viewer is concentrated in the center of the images, Stricker and Dimai [15] proposed to decompose each image into one elliptical region, corresponding to the center and four corner regions (with some fuzzy superposition between them). Other approaches consider a grid decomposition of the image into rectangular-shaped, resolution-dependent-sized regions. Each region can be used as an individual query item, providing thus the means of a partial query, as proposed by Malki, Boujemaa, Nastar and Winter [7].

III. COMPACT COLOR-TEXTURE DESCRIPTION

A classical texture description scheme is based on the use of the run-length matrix. A run-length, as defined in [3], [6], is a connected set of pixels, having the same scalar or vector value, and oriented according to a given direction θ. The run-length matrix M_θ accounts, for a specific image region, the number of run-lengths having all possible lengths (from one to the size of the image region according to the direction θ, n_θ) and values (according to the quantization used for the image values). Thus, $M_\theta(\mathbf{a},b)$ represents the number of sets of b successive, $\mathbf{a}$-valued, connected pixels, oriented according to the direction θ. Several directions θ can be simultaneously used for describing an image region; usually the horizontal, vertical and the two main diagonals are used. In the case of rather isotropic textures (such as the colored ornamental stones), the horizontal and vertical directions provide a sufficient description precision. The run-length matrix is not directly used for texture description, but some statistical parameters are computed on the basis of the $M_\theta(\mathbf{a},b)$. We proved elsewhere [17] that the classical parameters derived from the run-length matrix do not comply with the color texture description principles [9] and we have proposed an alternative description, based on the informational entropy of the joint run-length value and length distribution.

Moreover, the value distribution (color or gray-levels histogram) of the basic units composing the image (pixels or run-lengths) can be viewed as being modified by the spatial constraint of pixel connectivity that defines the run-length [17]. Thus, the process of formation of the run-length can be interpreted as the deformation of the initial image values distribution (measured by the image region histogram) into the marginal distribution of the run-lengths values. The difference between the two distributions can be measured according to several principles; the set of deformation measures can be considered as a feature vector for the run-length value distribution.

The entropy deformation measures constrained by the run-lengths are relevant for the textural content of the image. The color content must be described separately. We used the weighted-histogram approach [18]. The weighted histogram refines further the approach proposed by the CCV [12] by the partitioning of the image pixels in more than two classes, according to a local attribute (such as the edge strength, or the color importance degree). In order to keep the balance between the histogram size and the discrimination between pixels we propose to adaptively weight the contribution of each pixel of the image into the color distribution. This individual weighting allows a finer distinction between pixels having the same color and the construction of a weighted histogram that accounts both color distribution and statistical non-uniformity measures.

IV. THE IRIS SYSTEM

IRIS (Image Retrieval and Indexing System) is a prototype software toolbox for image database browsing and management. The IRIS system consists of a Matlab function set, which allow querying image databases according to image query examples, in order to retrieve images that are visually similar to the query. The query image can be internal or external to the indexed image database and is considered as a global query.

Like most indexing systems, IRIS performs the indexing of the database off-line, computing the content descriptor vectors for all the images within the specified image database. The image content descriptors are stored into an Image Database Descriptor (IDD) file, in a simple matrix form and linked to an Image Database Content (IDC) file, which lists the image filenames and locations. The image content descriptor vectors can be also stored as an expansion according to their principal components, by a Principal Component Analysis (PCA) or Karhunen-Loeve decomposition. The image content description vectors is thus computed on-line only for external image queries. The similarity between images is inferred according to the simple Euclidian (L2) distance between the corresponding image content description vectors. The query results are ranked according to their distance to the query image.

The graphical user interface of the IRIS system (see figure 1) is an image database browsing tool, which allows the user to visualize the content of a selected image database according to some pre-defined orders: the usual IDC-file order (alphabetical order of image filenames), a randomized selection order (a shuffle of the previous order) and the query-induced similarity order. All the aforementioned browsing types produce a linear image plot (see figure 4). If the PCA decomposition of the image descriptor vectors is used, the retrieval results can be visualized also in a two-dimensional image scatter-plot (figure 3), allowing a better understanding of the similarity relations between the images.

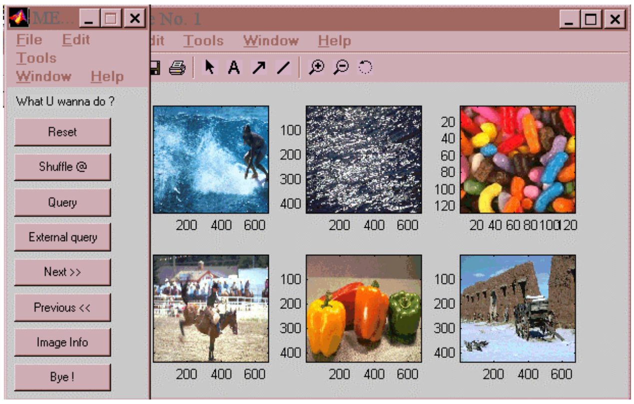

Fig. 1: Command window (at left) and image database browsing window of the IRIS system.

V. 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).

We evaluate the quantitative, objective retrieval performance of the proposed descriptors by the classical precision-recall curves. 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 figure

2, the proposed description scheme provides an excellent indexing performance.

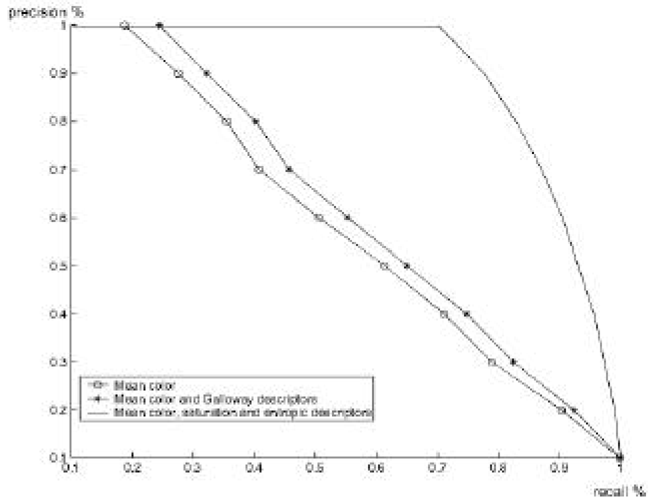

Fig. 2: Precision-recall curve for the retrieval performance within the Ornament image database for the proposed compact color texture descriptors (continuous line) compared to the indexing according to color alone (circle-marked line) and color and classical texture descriptors (star-marked line).

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. Table 1 presents the recognition rates for the two used databases (Ornament and Textures). Figures 5 and 6 present retrieval results for different queries with image examples that are external to the indexed image database.

Database	Recognition rate [%]			
	1-NN	3-NN	5-NN	7-NN
Ornament	97.00	93.43	89.86	85.64
Textures	90.11	85.89	80.78	75.44

VI. CONCLUSIONS

This paper presented an open system for image indexing and retrieval based by a set of interactive, easy-to-use Matlab functions. The system was aimed to primarily manage color texture image databases, by embedding compact color texture descriptors. Such descriptors are the entropy-based parameters computed from the run-length matrix and the deformation measures within the original, spatially unconstrained color distribution and the run-length constrained color distribution, extended with edge-strength weighted color histograms.

The proposed approach is more effective (in terms of descriptor size and retrieval/ recognition performance) than most classical color texture descriptors. We thus claim that the proposed compact color texture descriptor is a very good solution for effective, computationally inexpensive recognition and retrieval of color texture images. The test and experiments were focused on the management, match and control of ornamental stone images.

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Fig. 3: Two-dimensional image scatter-plot of images within the database, according to the similarity relations between the images and the image at the center. The distances within the image locations are proportional to the image similarity.

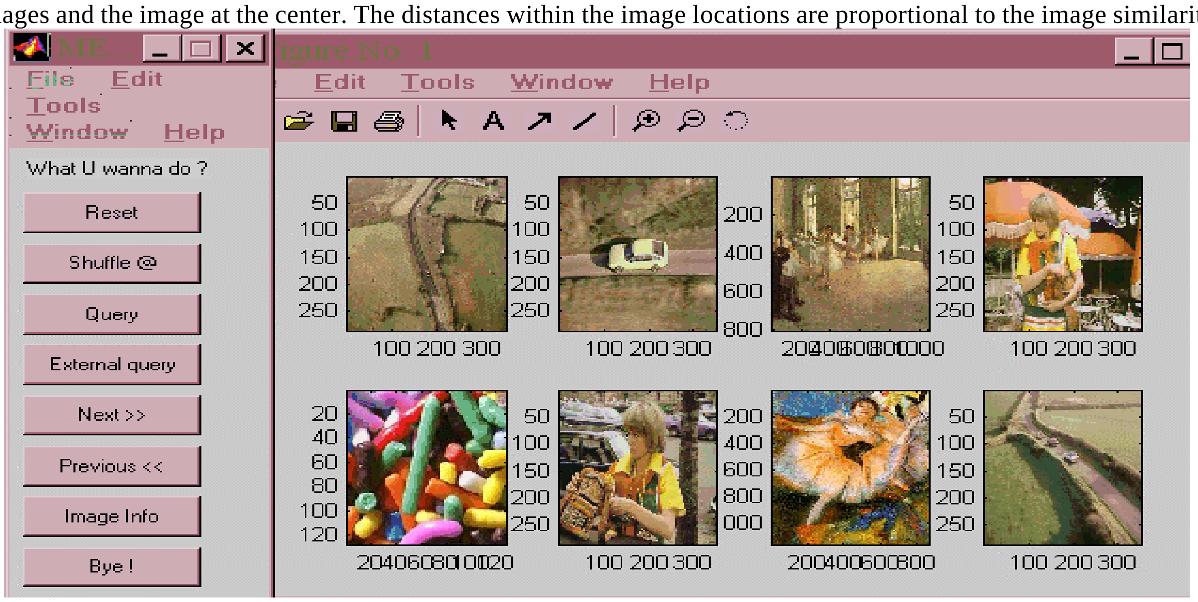

Fig. 4: Image database browsing according to the visual similarity with respect to the top-left image; the visualization effect is poorer as in the two-dimensional similarity visualization from figure 3.

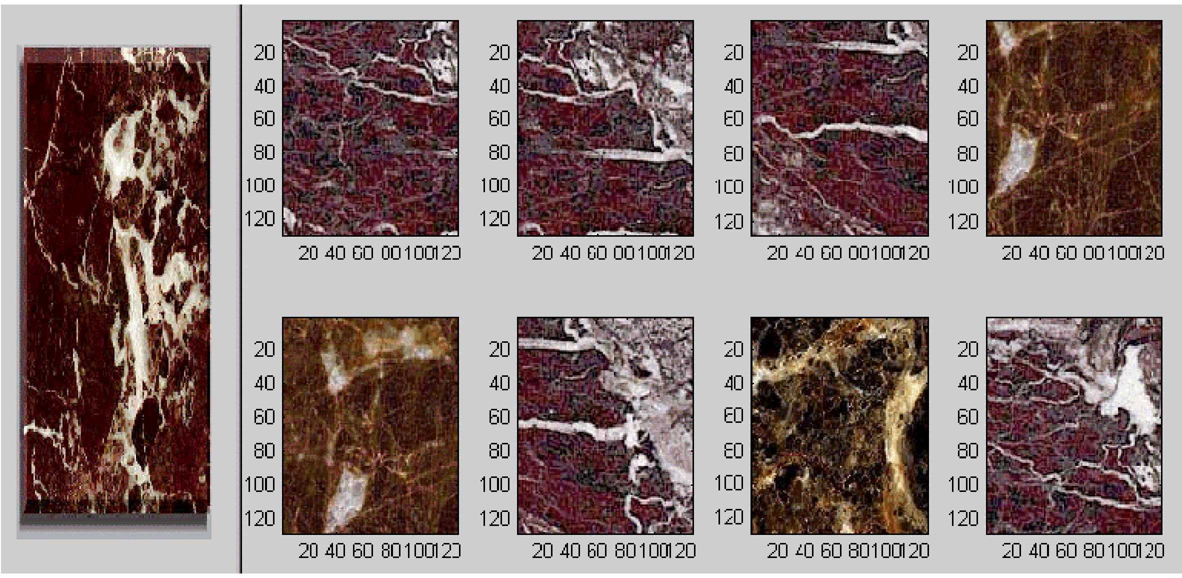

Fig. 5: External query by the image at the left (*rosso levanto* marble from Ankur Intl. Inc) and retrieved images from the Ornament image database (*rojolevanto*, *brecianouvella*, and *marronbrown* marbles from Marble and Granite Inc.).

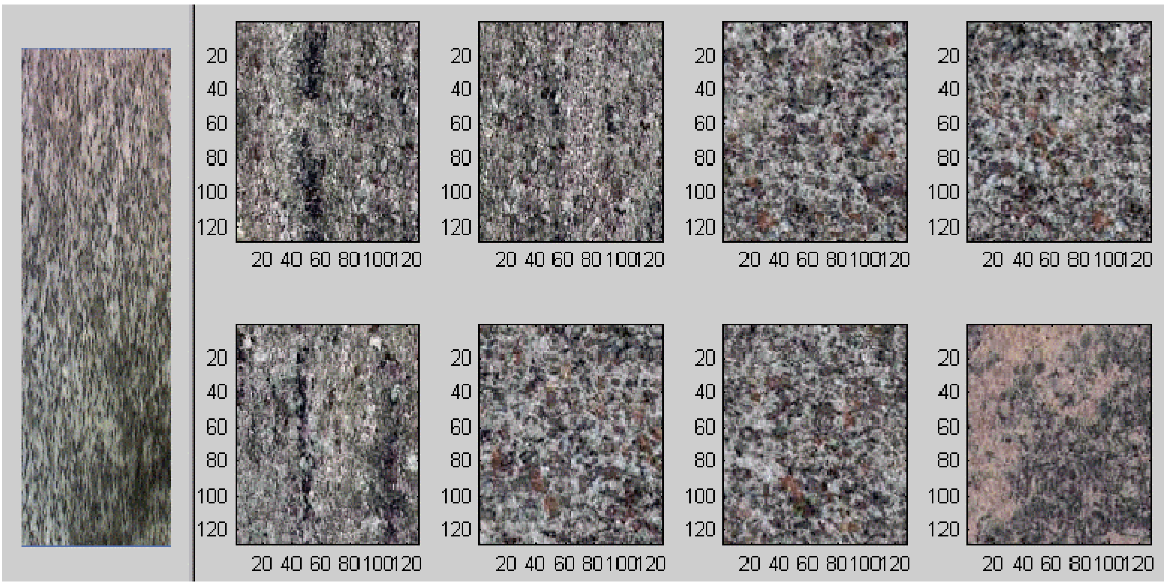

Fig. 6: External query by the image at the left (gray granite from the Pau School of Mines, France) and retrieved images from the Ornament image database (*tropicalgreenred*, *paradiso*, and *rainbow* granites from Marble and Granite Inc.).