NONPARAMETRIC APPROACH TO COLOR BASED IMAGE RETRIEVAL

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ABSTRACT

The rapid growth of image archives increases the need for efficient and fast tools that can retrieve and search through large amount of visual data. In this paper we propose an efficient method of extracting the image color content, which can serve as an image digital signature, allowing the efficient indexing and retrieval of large Internet-based multimedia databases. We applied the proposed method using the images from two Internet databases containing a collection of images of fine arts and a database of low resolution images, and show that the new method of image color representation is robust to image distorsions caused by resizing and compression and can be incorporated into existing web-based retrieval systems, that exploit the information on color content of digital images.

1. INTRODUCTION

Successful queries on large, distributed databases cannot rely on textual information only and therefore color image indexing is one of the most important methods used for automatic content based retrieval. In this paper we focus on the image indexing,which is based on the global color image distribution, which is applied for cases when the user provides a sample image for the query.

The majority of the systems exploiting the image color information work using various kinds of color histograms. However the histogram based approach has many drawbacks, as the histogram representation is sensitive to illumination changes, image resizing through interpolation and compression induced artifacts. Therefore, in this paper we propose a nonparametric approach to the problem of the estimation of the distribution of image colors.

2. COLOR HISTOGRAMS

Color indexing is a process through which the images in a database are retrieved on the basis of their color content. The indexing process must enable the automatic extraction of features, efficient assigning of digital signatures to images and effective retrieval of images within a database.

In order for an image retrieval system to retrieve images that are visually similar to the given query, a proper representation of the visual features is needed and a measure of the similarity between a given query and images from a database set has to be determined. Assuming that no textual information about the image content is given, image features such as color [1, 2, 3], texture [4, 5] and shape [6, 7] are commonly used.

These features are dependent on illumination, shading, resizing manipulations and compression induced artifacts. Thus, the visual appearance of an image is better described by the distribution of features, rather than by individual feature vectors.

Color feature has proven to be efficient in discriminating between relevant and non-relevant images. One of the widely used tools for image retrieval is the color histogram, which describes the distribution of colors in an image using a specific color space. The colors of an image are mapped into a discrete color space containing m colors. In this way, a color histogram is an m-dimensional vector, whose elements represent the number of pixels of a given color in an image.

In this paper we use the RGB color space, which although not perceptually uniform, is the most commonly used, primarily to retain the compatibility with computer acquisition and display systems. Let us assume a color image $\mathbf{Q}$ of size $n_1 \times n_2 = N$, composed of three RGB channels $\mathbf{Q} = \{Q^R_{i,j}, Q^G_{i,j}, Q^B_{i,j}\}$, $i = 1, \ldots, n_1$, $j = 1, \ldots, n_2$.

An image histogram in the RGB color space $H(r, g, b)$ is the approximation of the probability density function of the image RGB channels intensities

$$H(\rho, \gamma, \beta) = N^{-1} \# \left\{ Q^R_{i,j} = \rho, Q^G_{i,j} = \gamma, Q^B_{i,j} = \beta \right\},$$

where N is the total number of image pixels, and # denotes the number of pixels with color channel values $\{\rho, \gamma, \beta\}$.

For the analysis of colors which is independent of image brightness, it is convenient to transform the RGB values into normalized components r, g, b defined as: $r = R/I$, $g = G/I$, $b = B/I$, $I = R + G + B$, where $R, G, B \in [0, 255]$. The normalized color values can be expressed using only r and g values as $g = 1 - r - b$ and the normalization makes the r, g variables non-dependent on the brightness value I.

Using the normalized rg color space, the pixels can be mapped on a two-dimensional plane and a two-dimensional discrete histogram can be constructed, (Fig. 1): $\Phi(x, y) =$

$$= N^{-1} \# \left\{ \mathrm{int}\left(M Q^R_{i,j} / I_{i,j} \right) = x, \mathrm{int}\left(M Q^G_{i,j} / I_{i,j} \right) = y \right\}$$
$$= N^{-1} \# \left\{ \mathrm{int}\left(M r_{i,j} \right) = x, \mathrm{int}\left(M g_{i,j} \right) = y \right\},$$

$x, y = 0, \ldots, M$, where $(M + 1)$ determines the dimension of the 2-dimensional histogram, (for true-color images $M = 256$). The likeness between two images is often expressed through the similarity of their color histograms. One of the most popular ways to measure the similarity between two histograms H_P and H_Q is the Minkowski distance $\Delta(P, Q) = \sum_{x=0}^{M} \sum_{y=0}^{M} \{[\Phi_P(x, y) - \Phi_Q(x, y)]^p\}^{\frac{1}{p}}$. For $p = 2$ we obtain the Euclidean distance, which will be used in this work: $\Delta(P, Q) = \sum_{x=0}^{M} \sum_{y=0}^{M} \left\{[\Phi_P(x, y) - \Phi_Q(x, y)]^2\right\}^{\frac{1}{2}}$. Another measure of the similarity of two histograms is the histogram intersection defined as $\Delta(P, Q) = 1 - \sum_{x=1}^{N} \sum_{y=1}^{N} \min\{\Phi_P(x, y), \Phi_Q(x, y)\}$, which very often yields quite similar results.

3. NONPARAMETRIC COLOR DISTRIBUTION

The drawback of the histogram representation is that the shape of the histogram strongly depends on the method used for lossy image representation (Fig. 3) and on the image size or more precisely on the number of image pixels, as for small image sizes there is too few points to build proper histograms, which makes that the comparison of histograms is inapplicable.

* Supported by KBN GRANT 4T11F01824.

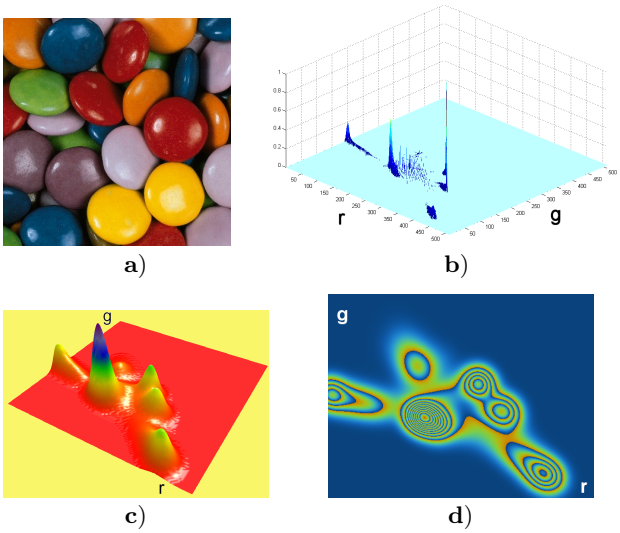

Figure 1: Illustration of the nonparametric probability density estimation: a) test image *PILLS*, b) its histogram in the rg color space, c) and d) present the visualization of the smooth kernel based estimation.

To alleviate the problems, we propose in this paper to estimate the color distribution not through the discrete histogram, but to use a smooth nonparametric estimate, based on the concept of nonparametric probability density estimation [8, 9]. In this formulation, the similarity measure between two estimates of the color distribution will be the mean distance between two surfaces of the two-dimensional kernel density estimation in the normalized rg color space, (Fig. 1).

Density Estimation describes the process of modelling the probability density function of a given sequence of sample values drawn from an unknown density distribution. The simplest form of density estimation is the histogram, however the main disadvantage of the histogram is its strong dependence on the chosen bin-width and the origin of the grid.

Kernel Density Estimation, avoids this disadvantage by placing a kernel function on every sample value in the sample space and then summing the values of all functions for every point in the sample space. This results in a smooth density estimates that are not affected by an arbitrarily chosen partition of the sample space, (Fig. 1, 2). The multivariate kernel density estimator in the q-dimensional case is defined as

$$\hat{f}_{\mathbf{h}}(\mathbf{x}) = \frac{1}{n}\sum_{i=1}^{n}\frac{1}{h_1\cdots h_q}\mathcal{K}\left(\frac{x_{i_1}-x_1}{h_1},\ldots,\frac{x_{i_q}-x_q}{h_q}\right),$$

with $\mathcal{K}$ denoting a multidimensional kernel function $\mathcal{K}\colon \mathbb{R}^q \to \mathbb{R}$ and $h_1,\ldots,h_q$ denoting bandwidths for each dimension and n is the number of samples in the sliding window. A common approach to build multidimensional kernel functions is to use a *product kernel* $\mathcal{K}(u_1,...,u_q) = \prod_{i=1}^{q} K(u_i)$, where K is a one-dimensional kernel function. Intuitively, the kernel function determines the shape of the 'bumps' placed around the sample values and the bandwidths $h_1,...,h_q$ their width in each dimension. If the bandwidth is the same in all dimensions, multivariate radial-symmetric kernel functions can be used,

$$\hat{f}_h(\mathbf{x}) = (nh^q)^{-1}\sum\nolimits_{i=1}^{n} K\left(\frac{||\mathbf{x}_i-\mathbf{x}||}{h}\right).$$

The shape of the approximated density function depends heavily on the bandwidth chosen for the density estimation.

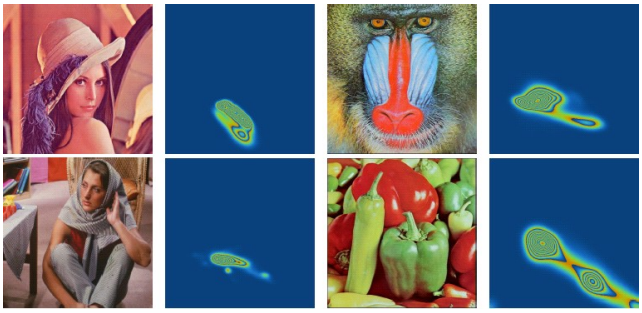

Figure 2: Kernel density estimation of the color distribution in the rg space for widely used test images.

Small values of h lead to spiky density estimates and too big values of h produce over-smoothed estimates that hide structural features. Choosing the Gaussian kernel function for K, the optimal bandwidth is in the one-dimensional case: $h^* = 1.06\hat{\sigma}n^{-\frac{1}{5}}$, where $\hat{\sigma}$ denotes the standard deviation, and for the q-dimensional case, [8, 9]

$$h^* = (4/(q+2))^{\frac{1}{q+4}}\,\hat{\sigma}n^{-\frac{1}{q+4}},$$

and as we work with the rg color space, therefore $q = 2$. In this work we used the Gaussian kernel, although we have obtained similar results using other kernel functions, [8, 9].

Using the kernel based estimation, a smooth estimate of the color distribution is obtained as shown in Figs. 1, 2 and Figs. 4, 5. As can be observed, the density distribution is insensitive to lossy image coding and resizing, which are the b a s i c operations performed when preparing large Internet multimedia databases. This color distribution can be used for the image retrieval purposes, as it can serve as a robust image signature, as depicted in Fig. 2, which shows the rg distributions of some well known color test images.

4. RESULTS

To evaluate the efficiency of the proposed color density estimation, we used as the testbed the images comprising the well known *WEBMUSEUM* Internet database, (available at http://www.ibiblio.org/wm). This art database contains a collection of about 3000 images of fine arts of various artists. Each image is coded in JPEG of moderate compression ratio (the blocking artifacts are hardly visible) with width or height of about 1000 pixels. Each image is accompanied by a thumbnail of width or height of 100 pixels, also compressed with JPEG.

From the database, the image of the painting *Starry Night* of V. van Gogh was chosen as the query image, (see Fig. 6). Using the kernel density estimation, we applied the Euclidean distance as the similarity measure and ordered the retrieved images according to the MSE values. The results are very promising, as the second image, most similar to the query, was another painting of van Gogh, (*Road with Cypress and Star*, Fig 6.3).

In the second experiment we used the thumbnail of the *Starry Night* image as query image. Although this picture is small (122×100) and heavily jpeged, the proposed scheme was able to find the image of full resolution, (first image in the ordered sequence) and the majority of images retrieved using the full resolution image, (Fig 7). Very similar results, were obtained using the histogram intersection method, so as expected the two methods of similarity evaluation yield comparable results.

Figure 8 shows the most similar images to the well known test image *LENA*. Surprisingly the most similar image from the *WEBMUSEUM* database was the *Girl with a Pearl Earring* of Vermeer. Figure 9 shows the sequence of most similar images from the database of J.Z. Wang, available at http://wang.ist.psu.edu/docs/related/, [10, 11].

5. CONCLUSIONS

In this paper we proposed a robust way of color density estimation. To enable fast retrieval of large databases we used the normalized rg color space. The experiments show that the method of nonparametric density estimation is insensitive to image compression and resizing. This makes the proposed framework interesting for image retrieval applications. Especially, the ability to retrieve images using a heavily distorted thumbnail is interesting, as it enables extremely fast retrieval of large databases. Future research will focus on the application of HSV color space and on the comparison of the proposed scheme with existing histogram based image retrieval techniques.

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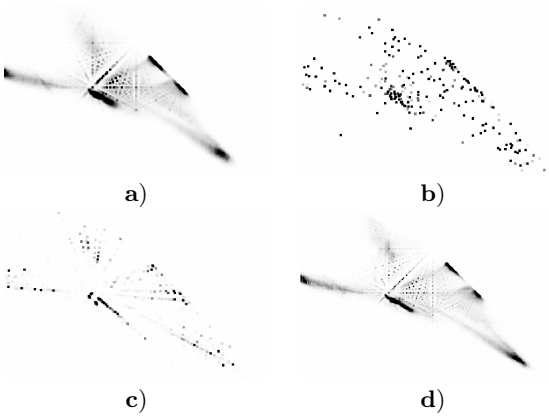

Figure 3: Influence of the compression methods on the color distribution in the normalized rg color space: **a**) test image *PILLS* of size 512×512, **b**) *PILLS* in GIF format, **c**) *PILLS* in JPEG format (compression ratio 78), **d**) *PILLS* in JPEG2000 (compression ratio 120).

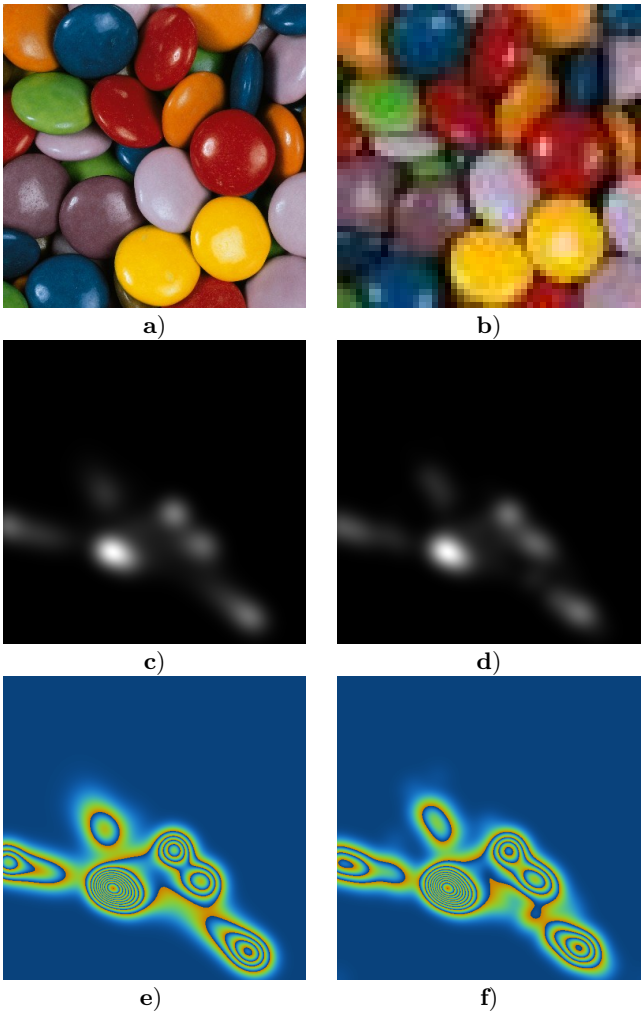

Figure 4: Robustness of density estimation to image scaling and compression: **a**) test image of size 512x512, **b**) resized and compressed (JPEG) image of size 48x48, **c**), **d**) gray-scale and pseudo-color representation, **e**) and **f**).

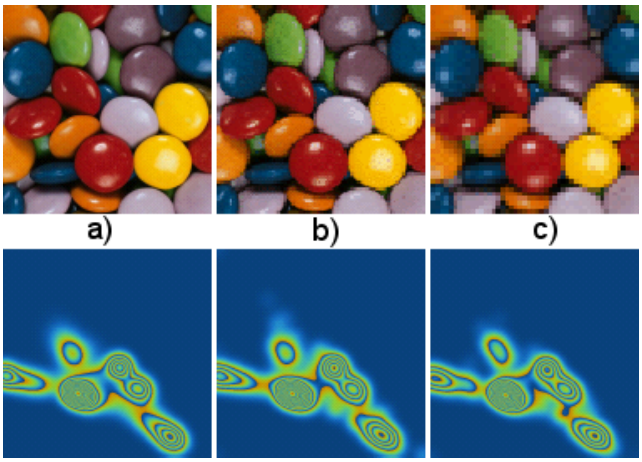

Figure 5: Density estimation in the rg color space for the test image of size 1536×1536 (**a**), 96×96 (**b**) and 48×48 (**c**), (bilinear interpolation was used).

Figure 6: Representative results for the query for images similar to the van Gogh "Starry Night" painting from the WEBMUSEUM database.

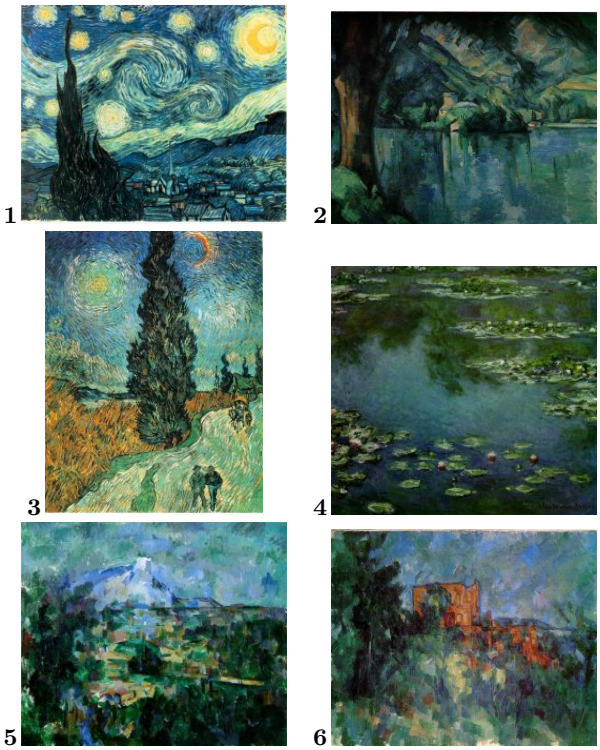

Figure 7: Representative results for the query for images similar to the thumbnail of size (122 x 100) of the van Gogh "Starry Night" painting, from the WEBMUSEUM database.

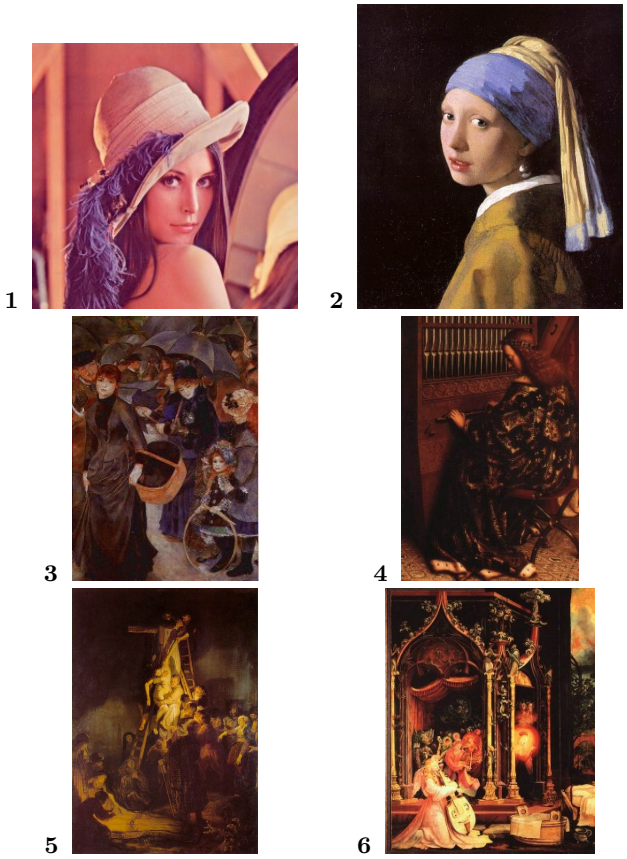

Figure 8: Representative results for the query for images from the WEBMUSEUM database similar to the *LENA* color test image.

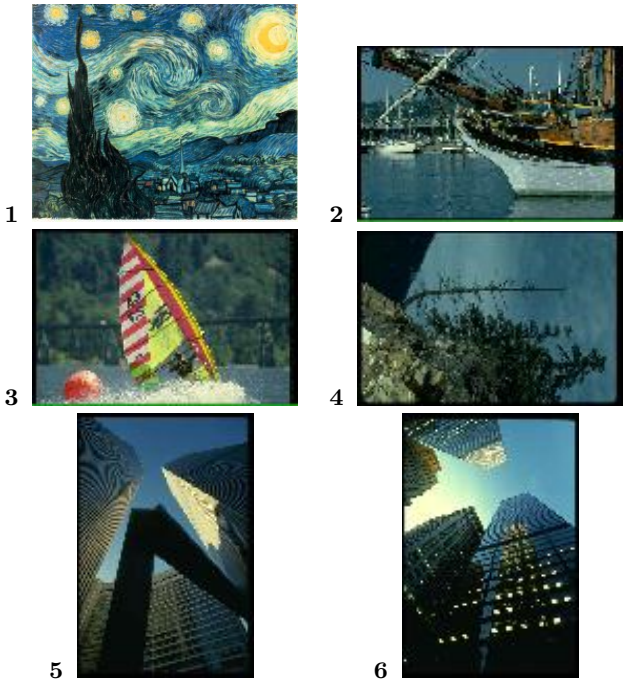

Figure 9: Representative results for the query for images from the database of Wang similar to the *Starry Night*.