Color Image Texture Indexing

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Abstract. The use of the image color information beyond color histograms has been limited for image retrieval. A reason is the lack of an accepted core basic color operation set on color images. With the grown interest in image retrieval applied to color images, new operators have been recently developed, having interesting properties. Opening distributions on images based on granulometries constitute an extremely useful tool in morphological tasks. Efficient techniques have been proposed for binary and grayscale images using linear openings. The present study extends the granulometry concept for color images. In addition, it addresses the development of a new morphological approach grounded on particle size distributions for color images and their use as an additional textural information to build queries over an image database.

1 Introduction

Multimedia information systems are becoming increasingly popular. They integrate text, images, audio and video and provide user desirable applications. One example is the image database system. Managing images for efficient retrieval and updating is a growing needed and challenging issue. Recently the interest in color images has grown due to the abundance of such color images on the WWW. The new interest has resulted in many new views on the subject.

Although color is heavily used as an important feature in image retrieval systems, its use has been limited to color histograms [13] [6] [12] mostly. Other features such as texture and shape are usually computed based on the intensity of the image or only on single color channel techniques. In [7] a technique for color image retrieval is described based on the Hue component only. In [16] wavelet based methods for texture are described using the separated color channels. In [6] the intensity of a color image is used to compute their texture, shape and moment features.

The reason for this limited use of the color content is resulted from the lack of theory about basic operators applied to color images. Furthermore, the *divide & conquer* approach does not exploit the correlation between color channels. Multichannel techniques that take into account that correlation have been reported to be more effective in [14] and [4].

Morphological methods like granulometries have been used to characterize size distributions and shapes on binary and grayscale images [10]. In this paper, we extend the notion of grayscale granulometries to color images based on the color opening and closing proposed in [4]. Moreover, we define a color pattern spectrum, i.e. the distribution of the object sizes, from which color image retrieval with texture can be computed.

The organization of this paper is as follows. Section 2 summarize the fundamentals of granulometries and size distributions. Section 3 describes the concept of color morphology, which is based on vector ranking concepts. Section 4 discuss about color indexing and extends the notion of granulometries to color images with the use of color pattern spectrum. In section 5 we demonstrate the results obtained using Monet [1] and show the practical use of the content-based image indexing running on a database of 6800 images. We conclude with section 6, summarizing the results and further research.

2 Granulometries and Size Distribution

Granulometries are based on the fact that a constant number of particles and constant amount of area or volume, at each scale level, are used to obtain particle size distributions. This idea can be developed further to obtain image signatures [2]. The following definitions are based on [10] and [5].

Definition 1 (Granulometry). *A granulometry can be interpreted as a collection of image operators $\{\Psi_t\}, t > 0$, such that Ψ_t is anti-extensive for all t, Ψ_t is increasing for all t, and $\Psi_t\Psi_s = \Psi_s\Psi_t = \Psi_{max\{t,s\}}$.*

It was observed by [15] that the most important example of granulometry is a finite union of decreasing openings (ϕ_t), each by a parameterized convex structuring element B:

$$\Psi_t(A) = (A \circ tB_1) \cup (A \circ tB_2) \cup \ldots \cup (A \circ tB_n) \tag{1}$$

Similarly, anti-granulometries, or granulometries by closings, can be defined as a finite union of increasing closings.

Definition 2 (Granulometric Size Distribution or Pattern Spectrum). *The granulometric size distribution or pattern spectrum of an image A, with respect to a granulometry $\{\Psi_t(A)\}, t > 0$ is a mapping $PS_{\Psi_t}(A)$ given by:*

$$PS_{\Psi_t}(A) = \Omega(\phi_t(A)) - \Omega(\phi_{t-1}(A)) \tag{2}$$

which is a discrete density. The density is called a granulometric size distribution or pattern spectrum.

2.1 Linear Grayscale Granulometries

Let us denote by $N_L(p)$ and $N_R(p)$ respectively the left and the right neighbors of a pixel p. The effect of an opening by a linear segment L_n, $n \geq 0$ on a grayscale image I:

Definition 3 (Line Segment). *A line segment S, of length $l(S)$, can be interpreted as a set of pixels $\{p_0, p_1, \ldots, p_{n-1}\}$ such that for $0 < i < n$, $p_i = N_R(p_{i-1})$.*

Definition 4 (Line Maximum). *A line maximum M of length $l(M) = n$ in a grayscale image I is a line segment $\{p_0, p_1, \ldots, p_{n-1}\}$ such that:*

$$\forall i, 0 < i < n, I(p_i) = I(p_1) \tag{3}$$

$$I(N_L(p_0)) < I(p_0) \ \ , \ \ I(N_R(p_{n-1})) < I(p_0). \tag{4}$$

The effect of a line opening of size n on M is that a new *plateau* of pixels is created at altitude $MAX\{I(N_L(p_0)), I(N_R(p_{n-1}))\}$. This plateau P contains M, and may be itself a maximum of $I \circ L_n$.

3 Multivalued Morphology

One of the basic ideas in mathematical morphology is that the set of all images constitutes a complete lattice. The concept of extrema, i.e. infimum and supremum, stems from this partial ordering relation. If the extrema exist for any collection of images, then that lattice is called a complete lattice.

Any morphological operator we apply to the color images can be applied to each component separately. This kind of marginal processing is equivalent to the vectorial approach defined by the canonic lattice structure when only extrema operators and their compositions are involved, inducing a totally ordered lattice. However, this morphological procedure fails because every color can be seen as a vector in a spatial domain and the extrema of the two vectors is a mixture of both colors. Besides, image components are highly correlated.

In [8], an approach grounded on vector transformations, followed by marginal ordering was introduced. An image is coded into another representation by means of a surjective mapping called h-adjunction. A major drawback in practice is that the extrema of each set of vectors are not necessarily unique. Recently, [3], [14], and [4] succeed in dealing with this question by ranking vectors, i.e. each vector pixel is represented by a single scalar value. When a bijective mapping is used, it induces a total ordering and determines clearly the extrema of each set of vectors. In this way, it is possible to perform any classical morphological filter on the coded image, and decode the result afterwards.

3.1 Ordering Color as Vectors

To extend the vector approach to color images, it is necessary to define an order relation which orders colors as vectors. This imposes a total ordering relationship achieved by the lexicographical ordering [1]. The structuring element for the vector morphological operations defined here is the set g, and the scalar-valued function

[1] An ordered pair (i, j) is lexicographically earlier than (i', j') if either $i \leq i'$ or $i = i'$ and $j \leq j'$. It is lexicographic because it corresponds to the dictionary ordering of two-letter words.

used for the reduced ordering is $h : R^3 \to R$. The operation of vector dilation is represented by the symbol $\oplus_v$. The value of the vector dilation of f by g at the point (x, y) is defined as:

$$(f \oplus_v g)(x, y) \in \{f(r, s) : (r, s) \in g_{(x,y)}\} \tag{5}$$

$$h((f \oplus_v g)(x, y)) \geq h(f(r, s)) \forall (r, s) \in g_{(x,y)} \tag{6}$$

Similarly, vector erosion is represented by the symbol $\ominus_v$, and the value of the vector erosion of f by g at the point (x, y) is defined as:

$$(f \ominus_v g)(x, y) \in \{f(r, s) : (r, s) \in g_{(x,y)}\} \tag{7}$$

$$h((f \ominus_v g)(x, y)) \leq h(f(r, s)) \forall (r, s) \in g_{(x,y)} \tag{8}$$

Vector opening is defined as the sequence of vector dilation after vector erosion, and vector closing is defined as the sequence of vector erosion after vector dilation.

Since the output of the vector filter depends on the scalar-valued function used for reduced ordering, the selection of this function provides flexibility in incorporating spectral information into the multi-valued image representation. When the bit-mix approach [3] is used, the transform h is based on the representation of each component of T in the binary mode. Let $T \in R^M$ with M components $t(i)$, each one represented on p bits $t(i)_j \in \{0, 1\}$ with $j \in \{0, \ldots, p\}$. The considered mapping h can then be written as follows:

$$t \preceq t' \leftrightarrow \begin{cases} h(t) = \sum_{j=1}^{p} \left\{2^{M.(p-j)} \sum_{i=1}^{M} 2^{M-i} t(i)_j\right\} \\ h(t') = \sum_{j=1}^{p} \left\{2^{M.(p-j)} \sum_{i=1}^{M} 2^{M-i} t'(i)_j\right\} \\ h(t) \leq h(t') \end{cases} \tag{9}$$

All scalar-valued functions lead to a family of images, parameterized by shape, size, and color, which could be useful for image retrieval.

4 Color Indexing

The extension of grayscale granulometries to color images is firmly established on multi-valued morphology. In this way, we can derive a color object size distribution based on color openings. Using these distributions as image descriptors makes searching for images with similar sized objects possible.

Since granulometries based on linear openings and closing are not rotation invariant we need to apply the same technique in a horizontal, vertical and diagonal direction. The results are merged into one pattern-spectrum using the maximum of the three, i.e.

$$PS_{\Psi_t}(A) = \max(PS_{\Psi_t}(h), PS_{\Psi_t}(v), PS_{\Psi_t}(d)) \tag{10}$$

One step further is the search for images with similar texture. We could derive a scale invariant description from the pattern spectrum that describes the texture of the image. We derive this scale invariant description, H, where each H_i is defined using the following equation.

$$H_i = \sum_{j=i} PS_j / PS_(i * j) \tag{11}$$

4.1 Color Pattern Spectrum

Texture and color are two important visual cues that give a large amount of information from surfaces in the scene. Although they share a common role in the scenes, they have been studied separately in computer vision due to the difficulty that both properties represent.

Texture is the visual cue due to the repetition of image patterns. It is used in several tasks such as classification of materials, scene segmentation and extraction of surface shapes from the texture variations. Much work in computer vision has focused on the texture perception problem. Psychophysical experiments and neurobiological evidences have provided the basis for the definition of computational models of texture perception [9].

The color visual cue is the result of the observation of an specific illuminant on a given surface using three different types of sensors. In computer vision, color has been used in region segmentation tasks, image classification, image database retrieval, surface chromatic constancy analysis, etc. The representation of color has been studied emphasizing the aspects of constructing perceptual spaces that allow applying the computer vision methods.

Several studies have been recently directed to the problem of co-joint representations for texture and color, some difficulties have arisen from the fact that three-dimensional color representation is not the best way to represent texture. Grouping texture and color representation reduces the amount of raw data presented by the image while preserving the information needed for the task in hand. This information reduction has to give a representation that allows to computationally dealing with the proposed task.

Searching images based on pattern spectrum requires a comparison method to be performed. Image retrieval systems use similarity measures to describe the similarity between two images. The proposed similarity measure is modeled after color histogram intersection and is robust to occlusion in the image. The same robustness is required for color image texture. We define the similarity between two pattern spectra as follows:

$$S(a,b) = \frac{\sum_{i=0}^{n} min(a_i, b_i)}{\sum_{i=0}^{n} a_i} \tag{12}$$

Many image retrieval operations require also searching on color content. On that account, we use color histograms to describe the image. Furthermore, we integrate similarity measures obtained from both color and texture using a linear combination with adjustable weights. So the user can control the importance of either one of the features easily.

5 Experimental Results

The experiments conducted were performed on a database taken from a CD-ROM of 6800 photographs. We calculate the pattern spectra for all twelve combinations of openings and closings in horizontal, vertical and diagonal directions for the color models RGB and HSI. We used the Monet[1] database system as our

Fig. 1. Histogram intersection results.

experimentation platform. This database systems was extended with an image data type and primitives [11].

Figure 1 shows the results of a query based on Histogram Intersection as described in [13]. Figure 2 shows the results of the same query by example images based on color pattern spectra. In both cases the top left image was the one selected, using the HSI model [2].

[2] Due to the costs of color printing and the inherent distortions associated with the size reduction and the printing process, the corresponding color plates will be made available through http://carol.wins.uva.nl/~ornellas/images/visual99.

Fig. 2. Color pattern spectra results.

6 Conclusions and Further Research

Color images should be treated as first class citizen, not as a special case of grayscale images. The information in the color triplet should not be broken into its channels. Splitting would waste valuable information. Using operators that preserve this information leads to better image retrieving feature vectors. We proposed the color pattern spectrum. It turns out to be an interesting retrieving feature, which could be efficiently computed. The experiments show that this texture feature will indeed improve the results made by an image retrieving system.

As future work, we like to point out that more features could be defined using these color operators. We like to investigate whether the color pattern spectrum could be used to search for partial images in the database.

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