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Wavelet Correlogram: A New Approach for Image Indexing and Retrieval

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Abstract: In this paper, a new approach for content-based image indexing and retrieval is presented. The proposed method is based on a combination of multiresolution analysis and color correlation histogram of the image. According to the new algorithm, the wavelet coefficients of the image are computed first using Daubechies3 wavelet. Then, monodimensional color correlogram of the horizontal and vertical wavelet coefficients are computed. Finally, the index vectors are constructed using these wavelet correlograms. The image retrieval results by applying the new method on a 1000 image database show a significant improvement in effectiveness and efficiency compared to the indexing and retrieval methods based on image correlogram or wavelet transform.

Key Words: Content-Based Image Indexing and Retrieval, Color Correlation, Multiresolution Analysis, Wavelet Correlogram.

1. Introduction

Digital image libraries and other multimedia databases have been dramatically expanded in recent years. Storage and retrieval of images in such libraries become a real demand in military, industrial, medical, and other applications [17]. Traditional methods for image indexing and retrieval are textual search engines that use image labels as keywords for searching. Regarding to the high rate of daily growing in multimedia databases, these methods are unable to process visual queries efficiently. Moreover, labeling images in a database is a cumbersome and imprecise task [18]. Therefore, content-based image indexing and retrieval (CBIR) is considered as a solution. In such systems, some features are extracted from every picture and stored as an index vector. Then, in retrieval phase, every index is compared using a similarity function, to find some similar pictures to the query image index [20].

Two major approaches can be identified in CBIR systems, including spatial and transform domain methods. The first approach usually uses simple features like color and shape [3], while in the second one, transformed images are used to extract some features. Among all features in the first approach, color is the most used signature for indexing [9]. Color histogram [27] and its variations were the first algorithms introduced in the pixel domain. However, color histogram is unable to carry local spatial information of pixels. Therefore, in such systems retrieved images may have many inaccuracies, especially in large image databases. For these reasons, two variations called image partitioning and regional color histogram were proposed to improve the efficiency of such systems. Image partitioning methods usually divide the

image into a fixed number of partitions, and color histogram is computed in each partition [25, 26]. In spite of larger computational cost, they don't provide a significant improvement in effectiveness. Because they are sensitive to translation, rotation and scaling. On the other hand, in regional color based methods the image is dynamically divided into different color regions [8, 18]. Although these methods have better performance compared to partitioning method, their dependency on the image segmentation may be considered as a disadvantage [20, 22]. To overcome the above mentioned problem, some methods using more semantic image information like color correlogram [4, 6, 12] and IRM [15] were introduced.

Shape based and color-shape based systems using snakes [11, 20], contours [19] and other boundary detection methods [22, 23], were proposed for CBIR. These systems are less sensitive to color information but have large computational cost.

Recently, wavelet based methods, which provide better local spatial information in transform domain have been used [13, 28]. Among all wavelets, Haar and Daubechies are the most used in CBIR, because of their fast computation and regularity, respectively. In SIMPLIcity method [14], Daubechies wavelets were used to extract wavelet coefficients in low components of every four frequency sub bands. Furthermore, the image is classified into different semantic classes by using a kind of texture classification method. In [17] a Daubechies wavelet was used to obtain a histogram of wavelet coefficients, based on three levels of wavelet. Then, every sub band histogram is stored to construct the feature vectors. Moreover, some experimental algorithms were used to reduce the computational complexity.

In the present work, Daubechies' wavelet coefficients are used first, to extract spatial-frequency information of the image. Then, the correlation of these coefficients in LH and HL sub bands is computed. The intuition behind is that in these regions the wavelet coefficients are usually related to edges of the image. Using these directional sub bands enables us to compute the spatial correlation more efficiently, while taking advantage of more semantic image information.

In the next section, the correlogram method is presented. In section 3, our new approach called "wavelet correlogram" is described. Experimental results will be presented in section 4. Finally, concluding remarks are given in the last section.

2. Color Correlogram

Color Correlogram, recently introduced by Huang *et al.* [12], is an approach for CBIR. The main advantages of this approach are: *i)* taking into consideration the spatial correlation of colors, *ii)* describing the global distribution of local spatial correlation of colors, *iii)* being easy to implement, and *iv)* producing fairly small size index [12].

Color correlogram of an image is a three dimensional matrix whose elements $\gamma(i, j, k)$ represent the probability of finding two pixels in the image with color c_i and c_j placed in a distance k of each other. Color correlogram expresses how the spatial correlation of pairs of colors changes with distance. This type of feature turns out to be robust in tolerating large variations in appearance of the same scene caused by changes of viewing position, background scene, partial occlusions and effects of camera zoom.

Let f be an $N \times N$ image (a square image for simplicity) consisting of M different colors $c_1, c_2, ..., c_M$. For a pixel $p_{(x,y)} \in f$, let $f_{(p)}$ expresses the pixel color and $f_c = \{p \mid f_{(p)} = c\}$. Therefore, $p \in f_c$ is equivalent to $p \in f$, $f_{(p)} = c$. For simplicity, $L_\infty - Norm$ is used to measure the distance between pixels. This measure is computed for two pixels $p_1(x_1, y_1), p_2(x_2, y_2)$ as follows:

$$|p_1 - p_2| = \max\{|x_1 - x_2|, |y_1 - y_2|\} \tag{1}$$

The histogram h of the image f is defined by:

$$h_{c_i}(f) = N^2 . \Pr\{[p \in f_{c_i}]\} \tag{2}$$

Assume that k is a specified distance and $i, j \in \{1, ..., M\}$. The correlogram of f is defined by:

$$\gamma(i,j,k) = \Pr_{p_1, p_2 \in f} \left\{ p_2 \in f_{c_j} \mid p_1 \in f_{c_i}, |p_1 - p_2| = k \right\} \tag{3}$$

According to Eq. (3), $\gamma(i, j, k)$ denotes the probability of finding pixels with color c_j at the distance k of the pixel with color c_i. The computation order of the above equation is $O(M^2 d)$, where d represents the number of different distances. Therefore, the correlogram computational cost seems to be too large for CBIR.
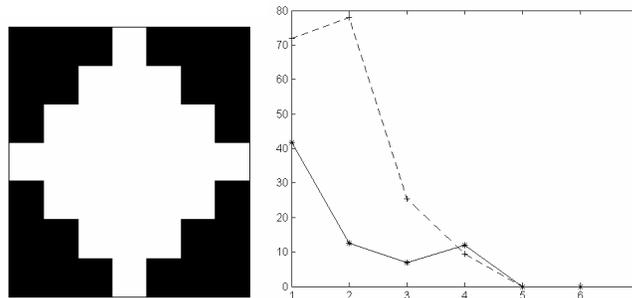
2.1 Autocorrelogram

The autocorrelogram of f represents spatial correlation between identical colors and is defined by:

$$\alpha(i, k) = \gamma(i, i, k) \tag{4}$$

This equation has only $O(Md)$ order and can be computed much faster than Eq. (3). Figures (1) and (2) show two different images ($M=2$, $N=7$) with the same histograms but completely different autocorrelograms.
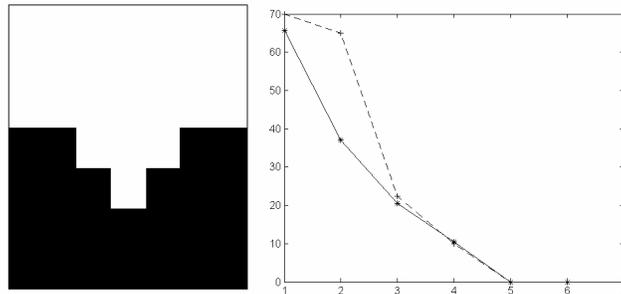
Figure 1. A sample binary image and it's autocorrelogram in four distances {1, 2, 3, 4}.

Figure 2. A binary image with the same histogram of Figure (1) and it's autocorrelogram in four distances {1, 2, 3, 4}.

According to [7], the autocorrelogram computing equations are:

$$\Gamma(i,i,k) = \left| \left\{ p_1, p_2 \in f_c \, | \, |p_1 - p_2| = k \right\} \right| \tag{5}$$

$$\alpha(i,k) = \frac{\Gamma(i,i,k)}{(h_{C_i}(f).8k)} \tag{6}$$

The denominator of Eq. (6) is the total number of pixels of color c_i at the distance k from any pixel with the same color and $8k$ is due to properties of $L\infty - norm$. Unfortunately, this equation has the order of $O(N^2 d^2)$. For this reason, some methods have been proposed [12] for fast computation of autocorrelogram.

3. Wavelet Correlogram

One of the most important properties of wavelet transform is space-frequency decomposition of the input signal. This property enables us to apply pixel domain tools, such as correlogram, to the wavelet coefficients. The wavelet correlogram approach is based on computing the spatial correlation of the image wavelet coefficients. In this way, the multiscale-multiresolution property of the wavelet transform and TR[1] invariancy of the correlogram will be combined. Consequently, the image indexes obtained by the wavelet correlogram method may have better discriminative performance.

3.1 Wavelet correlogram indexing algorithm

According to the wavelet correlogram indexing algorithm, the wavelet transform of the input image is computed first, in three consecutive levels. In the second step, the computed wavelet coefficients are quantized to a limited number of levels. Then, one dimensional autocorrelograms of vertical and horizontal quantized wavelet coefficients are computed. Finaly, one-dimensional autocorrelogram results are used to form feature vectors for image indexing. Figure (3) illustrates three major parts of the wavelet correlogram indexing algorithm, including preprocessing, processing and feature construction phases.
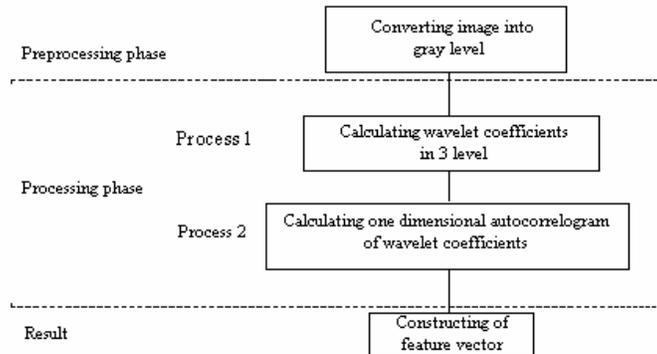
Figure 3. Wavelet correlogram indexing algorithm.

1- Translation and Rotation

Preprocessing

In our standard image database from Stanford University [14], one thousand color images from 10 different categories were provided in different sizes. In the preprocessing phase, color pictures in different input formats are first transformed to a unified gray level format. This transform is primarily aimed to reduce the input data dimensionality, while image content remains unchanged. It should be noted that the generality of the algorithm is preserved, since the same method may be applied to each color component of color images.

Wavelet transform

Wavelet decomposition is an important part of the image indexing algorithm. We use Daubechies wavelets for their regularity, separability and compact support properties. The result of the algorithm using Daubechies wavelet functions has shown better performance compared to the results obtained by other wavelet functions such as Harr wavelet. A comprehensive performance evaluation is currently being made in order to determine the most appropriate wavelet function to be used in the algorithm. Primary results demonstrated the importance of wavelet function regularity in the algorithm performance [14, 28].

Shift invariancy is another important requirement for image indexing algorithm. We have used a modified version of Mallat's DWT algorithm in order to ensure the shift invariancy of the wavelet decomposition [2, 3].

Wavelet Correlogram Computation

Wavelet transform results in four matrices in each resolution level containing wavelet coefficients computed using LL, HL, LH and HH filters. Since color-correlogram is primarily the computation of spatial correlation between different colors present in the image, a particular scheme for computing wavelet correlogram using wavelet coefficients is required. Logically, auto-correlogram computation on LH and HL matrices can be made in only one-dimension corresponding to the low-pass filter. Therefore, horizontal and vertical auto-correlograms will be computed on LH and HL matrices, respectively. A further advantage of this scheme is computational cost reduction compared to the two-dimensional auto-correlogram method proposed by Huang *et al* [12].

On the other hand, wavelet coefficients corresponding to HH filters have no significant spatial correlation. Therefore, there will be no need to compute the auto-correlogram based on these coefficients. Experimental results demonstrate that the diagonal auto-correlogram of wavelet coefficients computed on HH matrix, does not lead to any enhancement in indexing/retrieval performance.

The HL, LH and HH coefficients are real numbers with a large dynamic range. Quantization of wavelet coefficients is a necessary step before computing the auto-correlogram. In this work, we used four quantized levels as shown in figure (4). These levels are different in HL, LH (Fig. 4.a) and HH (Fig. 4.b) matrices.
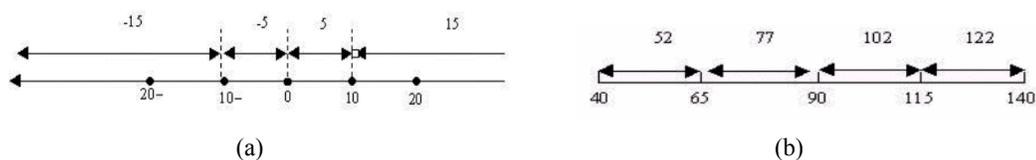

(a)   (b)

Figure 4. Quantization levels in a) HL, LH matrices and b) HH matrix.

Feature Vector Structure

Three versions of the wavelet correlogram algorithm have been investigated using specific feature vectors. In the first version, the coefficients of HL and LH matrices of each level have been used for computing feature vectors. In the second version, the coefficients of HH matrix, has been included in feature vector computation. Finally, in the third version, LL coefficients of the last resolution level have also been used in the construction of feature vectors.

The retrieval results proved the best performance for the first version of above mentioned indexing algorithms which is also the most computationally efficient one. The structure of feature vector in this version is simple and consists of some real numbers computed according to one-dimensional version of Eq. (6). The resulting feature vector contains 96 real numbers. Four level quantization of wavelet coefficients and computing auto-correlogram in four distances, provides 4*4=16 real numbers for each matrix. Two matrices in every level and total three levels, results in 16*2*3=96 total real numbers used in the feature vector structure. Since each real number needs eight bytes, the size of an image feature vector will be 768 bytes.

4. Results and Discussion

To do a systematical test on this algorithm, some query images were selected randomly from a 1000 image database downloaded from the SIMPLIcity site[1]. Pictures on the database are general purposed images including snap shots and landscapes from natural scenes such as tribes, elephants, flowers, dinosaurs and so on. Besides, each category contains 100 pictures in JPEG format and in the sizes of 384×256. To implement the test, five pictures of each category in the database were selected resulting in totally 50 test pictures. Two image query results are illustrated in figure (5).
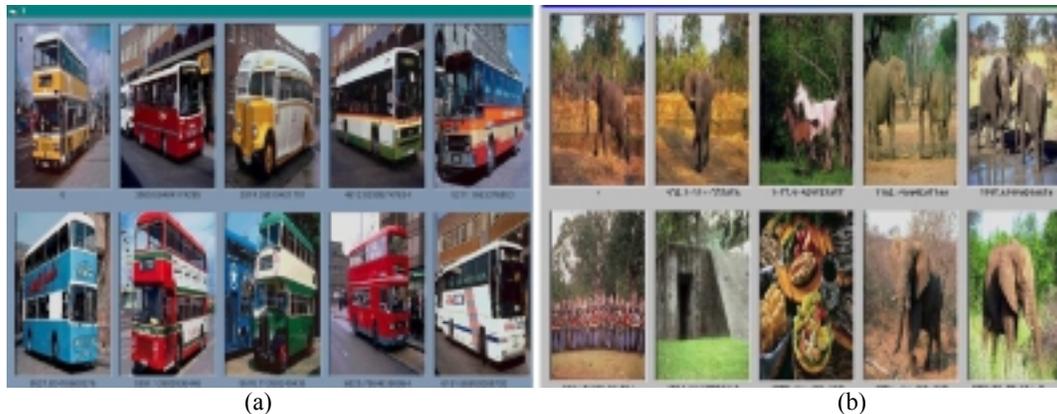

(a)   (b)

Figure 5. Results obtained from query image a) 359 and b) 575.

A retrieved image will be considered a match if it belongs to the same category of the query image. The developed indexing/retrieval software based on wavelet correlogram, outputs the ten best retrieved images in retrieval phase. Therefore, to compute the precision, between k retrieved images, for every query image the following equation has been used:

$$p_q = \frac{\sum_{i=10} n_i}{10} \times 100 \qquad n_i = \begin{cases} 1 & \text{Correct answer} \\ 0 & \text{Otherwise} \end{cases} \tag{7}$$

1- http://wang.ist.psu.edu/docs/related/

Also average precision is also computed using:

$$\widetilde{p} = \frac{\sum\limits_{i=5} p_i}{5} \times 100 \tag{8}$$

For all 10 averaged precision a total average is computed, then:

$$P_{tatal} = \frac{\sum\limits_{j=10} \widetilde{p}_j}{10} \times 100 \tag{9}$$

Table (1) shows the result obtained from applying the wavelet correlogram algorithm on the database.

Table 1. Results obtained form the wavelet correlogram algorithm.

Category	Query 1	Query 2	Query 3	Query 4	Query 5	Average
African people and villages	90% q=0	70% 25	90% 47	50% 62	90% 87	78%
Beaches	30% 101	90% 102	10% 109	60% 113	30% 166	44%
Buildings	90% 209	50% 210	80% 215	70% 251	80% 288	74%
Buses	80% 301	100% 321	90% 340	100% 359	70% 397	88%
Dinosaurs	100% 404	60% 422	100% 431	100% 452	80% 492	88%
Elephants	50% 503	60% 521	70% 560	60% 575	50% 596	58%
Flowers	50% 605	100% 637	90% 661	60% 677	100% 685	80%
Horses	80% 708	70% 718	90% 734	90% 766	90% 789	84%
Mountains and glaciers	40% 817	40% 832	50% 842	70% 865	50% 883	50%
Food	40% 910	60% 933	20% 952	50% 980	30% 998	40%
						68.4% Totaling.

5. Concluding remarks

In this work, a new approach in CBIR was presented. Two different tools from pixel and transform domains were combined to build the new method called wavelet correlogram. This method takes the advantages of both domains. A modified correlogram has a better efficiency compared to the color correlogram and also caused to carry more semantic information. Moreover, using wavelet makes it easy to cover the multiresolution analysis from the query image. So it became useful to compete the problems of pixel domain. Also categorization of the image frequencies has a significant effect to improve effectiveness by using correlation between image edges. Index vector based on wavelet correlogram is fairly small and independent of the picture size. The system developed based on this approach shows encouraging results and better performance compared to the color correlogram or wavelet based methods.

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