Enhanced Wavelet Correlogram Methods for Image Indexing and Retrieval

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ABSTRACT

In this paper, three new algorithms including optimal quantized wavelet correlogram (OQWC), wavelet CCV-correlogram (W3C), and color-W3C (CW3C) for content-based image indexing and retrieval are presented. In OQWC the threshold levels for wavelet coefficient quantization are optimized using an evolutionary process. W3C is an extension of OQWC that utilizes color coherence vectors (CCV) to include gray level and texture information in image index. Finally, CW3C is an extended version of W3C for effective color image indexing. The retrieval results obtained by the new methods on a 1000 image database demonstrate significant improvements in recall and rank compared to wavelet correlogram and SIMPLIcity methods.

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 industrial, medical, and other applications [1]. 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 [2]. In retrieval phase, every index is then compared (using a similarity criterion) to find some similar pictures to the query image [3]. Two major approaches including spatial and transform domain based methods can be identified in CBIR systems.

The first approach usually uses pixel (or a group of adjacent pixels) features like color and shape. Among all these features, color is the most used signature for indexing [4]. Color histogram [5] 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, three variations called image partitioning [6], histogram refinement [7], and color correlograms [8] were proposed to improve the effectiveness of such systems. In the histogram refinement approaches like CCV method introduced by Pass et al. [7], each histogram bar is divided into two or more parts according to its spatial color distributions. On the other hand, in color correlogram technique introduced by Huang et al. [8], the spatial color correlation of the image pixels are computed.

In the second approach, transformed data are used to extract some higher level features. Recently, wavelet based methods, which provide better local spatial information in transform domain have been used [1,9]. Daubechies wavelets are the most used in CBIR, because of their fast computation and regularity. In [1], Daubechies wavelets in three scales were used to obtain transformed data. Then, histograms of wavelet coefficients in each sub-band were computed and stored to construct indexing feature vectors. In SIMPLIcity method [9], the image is first classified into different semantic classes using a kind of texture classification algorithm. Then, Daubechies wavelets were used to extract feature vectors. A new method called wavelet correlogram (WC) is recently introduced by Abrishami *et al.* [10]. WC computes the correlogram of high frequency wavelet coefficients. That means it takes into consideration the relative position of the image features such as edges in different scales.

In the present work, we present various enhancements to WC method. Firstly, we propose OQWC method which optimizes the threshold levels for quantization of wavelet coefficients. Secondly, we propose a complementary technique called W3C based on CCV in order to include gray level and texture information to image index. Finally, CW3C extends the W3C method for effective indexing of color images.

This paper is organized as follows: in sections 2 and 3, histogram refinement and wavelet correlogram methods are reviewed. Section 4, presents our enhancements to wavelet correlogram. Experimental results are given in section 5. Finally, section 6 is devoted to concluding remarks.

2. HISTOGRAM REFINEMENT

In histogram refinement the pixels with same color in histogram are classified based on local features such as texture, orientation or distance from the nearest edge. CCV is an elaborated form of histogram refinement, in which histogram buckets are partitioned based on spatial coherence [7].

Suppose color space of image I is quantized to n distinct colors $\{c_1, c_2, \ldots, c_n\}$. The coherence measure classifies pixels as either coherent or incoherent

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depending on the size of the connected component in which the pixel is located. A pixel is coherent if the size of its connected component exceeds a fixed value ; otherwise, the pixel is incoherent.

Pass *et al.* [7] considered another characteristic for further refinement of the histogram. They defined the centermost 75% of the pixels as central and the others as non-central. Therefore, CCV subdivides each histogram bucket into four classes: coherent-central (τ_i), incoherent-central (β_i), coherent-noncentral (μ_i), and incoherent-noncentral (η_i). The feature vector in CCV will have $4\times n$ elements and is constructed as follows:

$$\widehat{CCV}(I)=\frac{1}{S}[(\tau_1,\beta_1,\mu_1,\eta_1),(\tau_2,\beta_2,\mu_2,\eta_2),\ldots,(\tau_n,\beta_n,\mu_n,\eta_n)], \quad (1)$$

where S is the number of image pixels. Obviously:

$$h_i=\tau_i+\beta_i+\mu_i+\eta_i,\;\; i=1,2,\ldots,n\,. \quad (2)$$

where h_i is the number of pixels in ith bucket of the image histogram.

3. WAVELET CORRELOGRAM

Wavelet correlogram, recently introduced by Abrishami *et al.* [10-11], combines the wavelet transform with color correlogram approach. Therefore, it inherits the multiscale multiresolution properties from wavelet and translation invariancy property from correlogram [8].

3.1. Wavelet correlogram indexing algorithm

Wavelet correlogram indexing algorithm consists of three steps as shown in Fig. (1). First, the discrete wavelet transform of the input image is computed in three consecutive scales using Daubechies' wavelets. Then, the wavelet coefficients are quantized to four levels. Finally, horizontal and vertical autocorrelograms of quantized coefficients are computed for LH and HL submatrices in each scale, respectively.

Quantization process discretizes the wavelet coefficients to four levels according to their values. Quantization levels corresponding to each wavelet scale used in [8] are illustrated in Fig. (2). As shown, small coefficients around zero are considered as noise and discarded. The criterion used for obtaining the threshold levels was the population of the remaining wavelet coefficients in each bin. That means each bin should consist of 25% of the non-zero wavelet coefficients.

Horizontal autocorrelogram of discretized LH coefficients with distances $k\in\{1,2,3,4\}$ is defined as follows:

$$\alpha(i,k)=\frac{\left|\left\{(x,y)\middle|LH(x,y)=c_i\,;LH(x,y+k)=c_i\ or\ LH(x,y-k)=c_i\right\}\right|}{2\times\left|\left\{(x,y)\middle|LH(x,y)=c_i\right\}\right|} \quad (3)$$

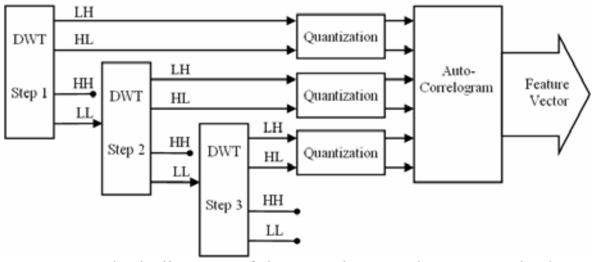

Fig. 1 Block diagram of the wavelet correlogram method.

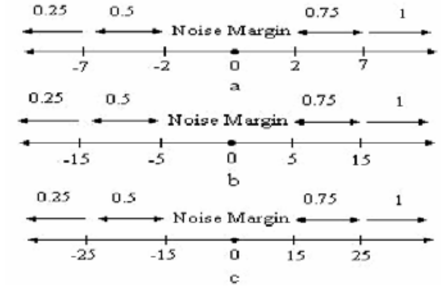

Fig. 2 Quantization thresholds in three consecutive wavelet scales of WC [10]: (a) scale one, (b) scale two, and (c) scale three.

where c_is are quantized levels. Indeed, $\alpha(i,k)$ is the probability of finding two pixels with quantization level c_i at the same row of LH in a distance $k\in\{1,2,3,4\}$ of each other. Vertical autocorrelogram is applied to HL coefficients in the same manner.

The structure of wavelet correlogram feature vector is simple. Computation of autocorrelogram in four distances ($k\in\{1,2,3,4\}$), provides $4\times4=16$ words for each matrix. Using two matrices (HL and LH) per scale and three consecutive scales result in $16\times2\times3=96$ words.

3.2. Wavelet correlogram retrieval algorithm

In the retrieval phase of wavelet correlogram, after computing the index of the input image, all the database images are sorted according to L_1 distance measure [11]. Then, N images with minimum distances are retrieved and illustrated.

4. PROPOSED APPROACHES

In the following subsections we explain our proposed methods in order to improve the effectiveness of the WC approach.

4.1. OQWC algorithm

In [10] and [12] an empirical method was presented for determining the threshold values for wavelet coefficients quantization (Fig. 2). In this work, we optimized the threshold values using a new family of genetic algorithms

(GA) called Evolutionary Society (ES). In this algorithm, an age parameter is defined for each chromosome. The chromosomes are able to obtain some experience during evolution. In other words, older chromosomes in the population are more experienced in the sense of their cost functions. The main advantage of the ES algorithm with respect to GA is its accelerated evolution speed. More details on the ES algorithm are out of the scope of this paper and will be given in our future paper. The final optimized quantization thresholds by ES are shown in Fig. (3). Simulation results with OQWC demonstrate better performance compared to WC (see Table 1).

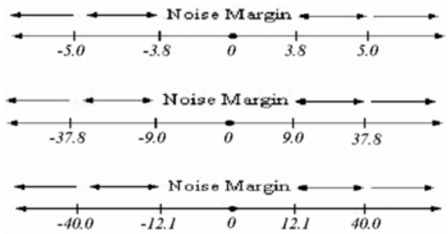

Fig. 3 ES optimized quantization thresholds in three consecutive wavelet scales.

4.2 W3C algorithm

In order to include gray level and texture information, CCV is applied to LL submatrices of OQWC in different wavelet scales. Elements of each LL submatrix are quantized uniformly to n=8 levels and δ is defined as:

$$\delta = \mathrm{S}/1280\,, \tag{4}$$

where S is the total number of input image pixels. Fixed δ for all wavelet scales provides multiscale information for gray level and texture of the image. In more details, a pixel is coherent in the fist, second, and third scales, if the size of its connected component in the image, exceeds 4δ, 16δ, and 64δ, respectively. Consequently, the proposed algorithm called Wavelet CCV-Correlogram (W3C) computes in each scale, CCV feature of LL submatrix in addition to the autocorrelogram of LH and HL submatrices. Therefore, the final feature vector will have $96 + 3\times 8\times 4 = 192$ elements (words).

4.3 CW3C algorithm

Before applying W3C method to color images, they should be converted to gray-level format. CW3C is an extension of W3C to handle color images in a more effective way. The CW3C index consists of three parts. Each part is determined by applying W3C to each color channel of the color image in CIE-Luv color space [13]. Hence, CW3C feature vector size will be $3\times 192 = 576$ words.

4.4 Proposed retrieval method

Let $X_r = [x_{rj}]_{j=1}^{p}$ and $X_q = [x_{qj}]_{j=1}^{p}$ be the feature vectors of two different images where p is the feature vector length. We defined a new dissimilarity measure as follows:

$$d_{\mu}(r,q) = \sum_{j=1}^{p} w_j \left| \frac{x_{rj} - x_{qj}}{\mu + x_{rj} + x_{qj}} \right|, \tag{5}$$

where $w_j \ (j = 1,2,\ldots,p)$ specifies the weight of each component of the feature vector. A genetic algorithm is used in order to optimally determine these weights [14]. Experimental results of this paper have been obtained using this optimizing algorithm.

5. RESULTS AND DISCUSSION

We used a subset of COREL database with 1000 images for evaluation of the developed algorithms[1]. The database images are categorized in 10 classes as listed in Table (1). Fig. (4) illustrates two query results using CW3C.

A retrieved image has been considered a match if it belongs to the same class of the query image. The developed indexing retrieval software, including the proposed algorithms, provides N (specified by the user) best retrieved images based on the proposed dissimilarity measure (Eq. 5) for each query.

The performance of the proposed methods including OQWC, W3C, and CW3C are compared with WC [10] and SIMPLIcity [9] algorithms. Recall R and rank C for a query image $I_k \ (k = 1,2,\ldots,1000)$ are defined as:

$$R(I_k) = \left| \{ I_i \mid Rank(I_i) < 100, i = 1,\ldots,1000 \} \right| / 100\,, \tag{6}$$

$$C(I_k) = \sum_{I_i \in A(I_k)} Rank(I_i) \Big/ \left| A(I_k) \right| \cdot \tag{7}$$

where $A(I_k)$ represents the set of all matched images with I_k and $|A|$ gives the number of its members. The average recall and rank for images belonging to the qth category (A_q) have been computed by the following equations:

$$\overline{R}(q) = \sum_{k\in A_q} R(I_k) \Big/ \left| A_q \right|, \quad q = 1,2,\ldots,10\,, \tag{8}$$

$$\overline{C}(q) = \sum_{k\in A_q} C(I_k) \Big/ \left| A_q \right|, \quad q = 1,2,\ldots,10 \cdot \tag{9}$$

Finally, the total average recall and rank are determined as:

$$\overline{R} = \sum_{q=1}^{10} \overline{R}(q) \Big/ 10\,, \tag{10}$$

$$\overline{C} = \sum_{q=1}^{10} \overline{C}(q) \Big/ 10 \cdot \tag{11}$$

Table (1) compares the results of the developed algorithms with WC and SIMPLIcity methods. All proposed algorithms show better performance than WC. Furthermore, the results obtained by CW3C algorithm demonstrate significant improvement with respect to the results reported for SIMPLIcity.

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2. From SIMPLIcity site http://wang.ist.psu.edu/docs/related/

Table 1 Results of the proposed algorithms including OQWC, W3C, and CW3C compared to SIMPLIcity and WC.

		SIMPLIcity		WC		OQWC		W3C		CW3C	
	Category	$\bar{R}$ (%)	$\bar{C}$	$\bar{R}$ (%)	$\bar{C}$	$\bar{R}$ (%)	$\bar{C}$	$\bar{R}$ (%)	$\bar{C}$	$\bar{R}$ (%)	$\bar{C}$
1	**Africans**	47.4	177.6	29.5	288.4	31.1	283.0	38.5	233.0	44.5	212.0
2	**Beaches**	32.3	241.0	28.9	340.8	28.7	335.5	31.1	300.9	28.9	325.8
3	**Buildings**	32.9	260.9	29.3	315.8	30.5	308.6	29.5	293.3	37.0	268.1
4	**Buses**	36.2	259.6	62.7	112.7	63.9	109.2	68.3	94.5	83.1	69.2
5	**Dinosaurs**	97.9	49.7	26.2	420.7	28.8	410.5	72.9	138.4	65.4	131.9
6	**Elephants**	40.0	196.3	30.9	241.0	30.4	236.2	43.0	180.7	50.7	141.5
7	**Flowers**	40.0	298.1	58.6	150.3	65.1	126.4	66.7	110.3	53.3	150.2
8	**Horses**	71.6	91.9	36.7	266.9	40.0	264.9	38.9	250.2	57.2	151.9
9	**Mountains**	34.2	229.8	23.0	334.7	25.0	325.3	27.2	288.7	39.8	233.5
10	**Food**	33.7	270.8	34.7	242.3	36.5	236.8	36.9	226.4	60.8	136.8
	Total	46.6	207.6	36.1	271.4	38.0	263.6	45.3	211.63	**52.1**	**182.1**

(a)

(b)

Fig. 4 Retrieval results obtained for query images (a) 781 and (b) 927 using CW3C.

5. CONCLUDING REMARKS

In this paper, three new methods for CBIR were presented. OQWC improves WC by optimizing quantization of wavelet coefficients. W3C takes into consideration gray level and texture information by including a CCV feature computed for low frequency wavelet coefficients. Finally, CW3C is an extension of W3C for effective indexing of color images. Simulation results demonstrate that all proposed algorithms performs better than WC. Furthermore, CW3C has given a significant improvement compared to SIMPLIcity.

6. ACKNOWLEDGEMENT

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