A NEW IMPROVED WAVELET CORRELOGRAM METHOD FOR IMAGE INDEXING AND RETRIEVAL

M. Saadatmand-Tarzjan
Tarbiat Modares University
saadatmand@kiaeee.org

H. Abrishami Moghaddam
K.N.Toosi University of Technology
moghadam@eetd.kntu.ac.ir

Abstract: In this paper, a new algorithm called wavelet correlogram-CCV (W3C) for content-based image indexing and retrieval is presented. W3C is an extension of wavelet correlogram that utilizes color coherence vectors (CCV) to consider texture information in addition to the shape for gray-level images. Additionally, a new distance measure that is optimized by genetic algorithms is proposed. The retrieval results obtained by the new method on a 1000 non-medical image database demonstrate significant improvements in recall and rank compared to wavelet correlogram and SIMPLIcity methods. Also, simulations on a 1030 medical image database show considerable good performance.

Key Words: Content Based Image Indexing and Retrieval, Wavelet Correlogram, Color Coherence Vector, Genetic Algorithms, Medical Imagebases.

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, in the indexing algorithm, some features are extracted from every picture and stored as an index vector [2]. Then, in the retrieval algorithm, every index is compared (using a similarity criterion) to find some similar pictures to the query image [3].

Various indexing algorithms based on different image features such as color [4-6], texture [7], and shape [8] have been developed. Among all these features, color is the most used signature for indexing. Color histogram and its variations were the first algorithms introduced in the pixel domain [9]. Despite its efficiency and insensitivity to a little changes of view point, the 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 [4], histogram refinement [5], and color correlograms [6] were proposed to improve the effectiveness of such systems. In the histogram refinement approaches like color coherence vector (CCV) algorithm introduced by Pass et al. [5], each histogram bar is divided into two or more parts according to its spatial color distribution. On the other hand, in the color correlogram technique introduced by Huang et al [7], the spatial color correlation of the image pixels are computed.

In the above algorithms, the feature vectors are constructed using spatial domain information. Another possibility is the use of transformed domain data to extract some higher-level features [10]. Wavelet based methods, which provide space-frequency decom-

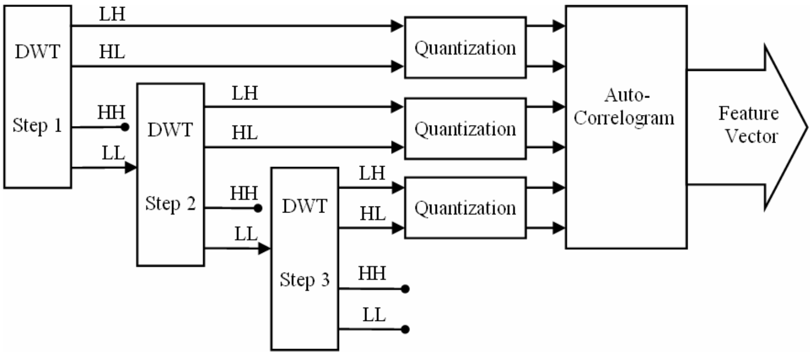

Fig. 1. Block diagram of the wavelet correlogram method.

position of the image have been used [11, 12]. Daubechies' wavelets are the most used in CBIR for their fast computation and regularity. In [10], Daubechies' wavelets in three scales have been used to obtain the transformed data. Then, histograms of the wavelet coefficients in each sub-band have been computed and stored to construct the feature vector. In SIMPLIcity [11], the image is first classified into different semantic classes using a kind of texture classification algorithm. Then, Daubechies' wavelets are used to extract feature vectors. Recently, a wavelet-based CBIR system called wavelet correlogram has been introduced by Abrishami Moghaddam et al. [12]. Wavelet correlogram computes the correlogram of high-frequency wavelet coefficients. Indeed, it takes into consideration the relative position of the image features such as edges in different scales. This system will be briefly reviewed in Section 2.

In the present work, a new algorithm is proposed. This algorithm enhance wavelet correlogram by two improvements: first, the feature vector is extended to include texture information using CCV in addition to the shape features and second, a new distance measure is utilized for the retrieval algorithm that is optimized by genetic algorithms (GA).

This paper is organized as follows: in Section 2 the wavelet correlogram method is reviewed. Section 3 presents our enhancement of wavelet correlogram feature vector to include texture information in addition to the shape. Section 4 appears the proposed evolutionary-optimized distance measure. Experimental results are given in Section 5. Finally, Section 6 is devoted to concluding remarks.

2. Wavelet Correlogram

Wavelet correlogram (WAC), recently introduced by Abrishami et al. [12, 13], combines the wavelet transform with color correlogram approach. Hence, it inherits the multiscale multiresolution properties from the wavelet transform and translation invariancy property from the correlogram algorithm [6].

2.1 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, the horizontal and vertical auto-correlograms of quantized coefficients are computed for the **LH** and **HL** submatrices in each scale, respectively.

Quantization process discretizes the wavelet coefficients to four levels according to their scale. The optimized quantization thresholds [14] corresponding to each wavelet scale are illustrated in Fig. 2. As shown, small coefficients around zero are considered as noise and discarded.

The horizontal autocorrelogram of discretized **LH** coefficients with distance $k \in \{1,2,3,4\}$ is defined as follows,

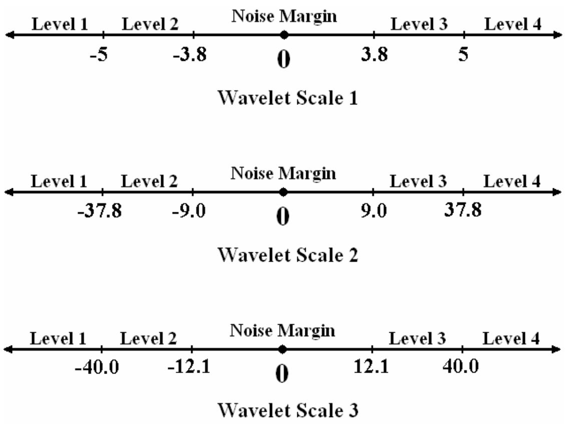

Fig 2. Optimized quantization thresholds of the wavelet correlogram [14].

$$\alpha_h(i,k) = \frac{\left|\{(x,y) \mid \mathbf{LH}(x,y) = c_i, \mathbf{LH}(x,y+k) = c_i \text{ or } \mathbf{LH}(x,y-k) = c_i\}\right|}{2 \times \left|\{(x,y) \mid \mathbf{LH}(x,y) = c_i\}\right|} \tag{1}$$

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

$$\alpha_v(i,k) = \frac{\left|\{(x,y) \mid \mathbf{HL}(x,y) = c_i, \mathbf{HL}(x+k,y) = c_i \text{ or } \mathbf{HL}(x-k,y) = c_i\}\right|}{2 \times \left|\{(x,y) \mid \mathbf{HL}(x,y) = c_i\}\right|} \tag{2}$$

The structure of wavelet correlogram feature vector is simple. According to Fig. 2, wavelet coefficients are quantized into four levels in each scale. Hence, the computation of autocorrelogram in four distances ($k \in \{1,2,3,4\}$) provides $4 \times 4 = 16$ words for each matrix. Using two matrices (**HL** and **LH**) per scale and three consecutive scales result in $P_{\mathrm{WAC}} = 16 \times 2 \times 3 = 96$ words.

2.2 Retrieval Algorithm

In the retrieval phase of wavelet correlogram, after computing the index of the input image, all database images are sorted according to L_1 distance measure [12]. Then, N images with the minimum distances are retrieved and shown for user.

3. Feature Vector Enhancement

For extending the wavelet correlogram feature vector to include texture information, the CCV algorithm (a histogram refinement method) is utilized.

3.1 Histogram Refinement

In histogram refinement methods the pixels with same color in the 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 bars are partitioned based on spatial coherency [5].

Suppose that 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 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 specified threshold δ otherwise, the pixel is incoherent.

Pass *et al.* [5] considered another characteristic for more refinement of the histogram. They defined the centermost λ=75% of the pixels as central and the others as noncentral. Therefore, CCV subdivides each histogram bar into four parts: coherent-central (τ_i), incoherent-central (β_i), coherent-noncentral (μ_i), and incoherent-noncentral (η_i) as follows:

$$\hat{\mathbf{CCV}}(I) = \frac{1}{S}[(\tau_1,\beta_1,\mu_1,\eta_1),(\tau_2,\beta_2,\mu_2,\eta_2),\ldots,(\tau_n,\beta_n,\mu_n,\eta_n)] \tag{3}$$

where S is the total number of image pixels. It is obvious that:

$$h_i = \tau_i + \beta_i + \mu_i + \eta_i, \quad i = 1,2,\ldots,n \tag{4}$$

where, h_i is the i-th bar of the image histogram.

3.2 Adding Texture Information

In order to add texture information, CCV is applied to **LL** submatrices of wavelet correlogram in different wavelet scales. Elements of each **LL** submatrix are quantized uniformly to n=8 levels and δ is experimentally defined as follow,

$$\delta = \mathrm{S}/1280 \tag{5}$$

Fixed δ for all wavelet scales provides multiscale information for 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 that called wavelet correlogram-CCV (W3C) computes CCV feature of the **LL** submatrix in each scale in addition to the autocorrelogram of **LH** and **HL** submatrices. Therefore, its final feature vector consists of $P_{\mathrm{W3C}} = 96 + 3\times 8\times 4 = 192$ words.

4. Proposed Distance Measure

Let $\mathbf{X}_r = [x_{rj}]_{j=1}^{P}$ and $\mathbf{X}_q = [x_{qj}]_{j=1}^{P}$ be the feature vectors of the images $\mathbf{I}_r$ and $\mathbf{I}_q$ where P is the feature vector length:

$$\mathbf{X}_j = \mathrm{indexing}(\mathbf{I}_j), \qquad j = 1,2,\ldots,|\mathbf{A}| \tag{6}$$

where $|\mathbf{A}|$ returns the cardinality of the reference imagebase **A**. We define a new distance measure called proportional weighted difference (PWD), instead of L_1 in the original work [13], as follows,

$$d_1(\mathbf{X}_r, \mathbf{X}_q; \mathbf{W}) = \sum_{j=1}^{P} w_j \left| \frac{x_{rj} - x_{qj}}{1 + x_{rj} + x_{qj}} \right| \tag{7}$$

where $\mathbf{W} = [w_1, w_2, \ldots, w_P]$ specifies the weighting coefficients of the feature vector components. A genetic algorithm is used in order to optimally determine these weighting coefficients. All of the experimental results in this paper have been obtained using this optimized distance measure.

4.1 Optimizing Proposed PWD Measure

In the proposed genetic algorithm for optimizing the PWD weighting coefficients, each chromosome consists of p genes and each gene specifies the value (between 0 and 1) of its corresponding weighting coefficients in PWD. In other words, we have:

$$\mathbf{C}_j = [c_{j,1}, c_{j,2}, \ldots, c_{j,P}], \qquad j = 1,2,\ldots,K_{\mathrm{GA}} \tag{8}$$

where $\mathbf{C}_j$ indicates j-th chromosome of the population and K_{GA} is the population size. In the proposed genetic algorithm, the average rank measure defined according to Equation (9) is used to evaluate chromosomes:

$$\overline{\Gamma}(\mathbf{C}_j) = \frac{1}{|\mathbf{A}|} \sum_{k\in\mathbf{A}} \Gamma(\mathbf{I}_k, \mathbf{C}_j), \qquad j = 1,2,\ldots,K_{GA} \tag{9}$$

where the function $\Gamma(\mathbf{I}_k, \mathbf{C}_j)$ computes the average rank of all images in the subimagebase $\mathbf{A}_k$ as follows,

$$\Gamma(\mathbf{I}_k, \mathbf{C}_j) = \sum_{q\in\mathbf{A}_k} \frac{Rank(\mathbf{I}_q; \mathbf{I}_k, \mathbf{C}_j)}{|\mathbf{A}_k|} \tag{10}$$

where the subimagebase $\mathbf{A}_k$ includes all images that are matched with the query image $\mathbf{I}_k$ in the reference imagebase **A** and the function $Rank(\mathbf{I}_q; \mathbf{I}_k, \mathbf{C}_j)$ returns the rank of image $\mathbf{I}_q$ (for the query image $\mathbf{I}_k$) among all images of **A** based on the proposed distance measure d_1 when its weights are initialized by the genes of the j-th chromosome as follows,

$$w_q = c_{j,q}, \qquad q = 1,2,\ldots,P \tag{11}$$

Comparing to the other evaluation measures such as average precision [9] and recall [11], the average rank is preferred in the proposed genetic algorithm since it considers the ranks of all images in the reference imagebase.

The mathematical one-point crossover operator and the conventional mutation operator [15] (with the mutation probability P_{m}) are used in the proposed genetic algorithm. Also, the initial population is generated based on seeding method [16].

In nature, the evolution tends to remove kinds that have less conformity with the environmental conditions instead of keeping kinds that have more conformity [17]. In other words, removing poor kinds is more effective than keeping elite ones in evolution. In the proposed genetic algorithm similar to GENITOR [18], in each generation, only two chromosomes are selected as parents and hence, only two offspring are generated.

One of these parents is selected by tournament operator (with tournament size K_{Tour}) [15] and the other parent is randomly chosen from the current population. The next population is generated by inserting the generated offspring, which are not similar to the current population chromosomes (for guaranteeing the population diversity), instead of the two chromosomes that have the worst evaluation values in the current population. The chromosomes $\mathbf{C}_p$ and $\mathbf{C}_q$ are similar, if we have,

$$\sum_{j=1}^{P} \left| c_{p,j} - c_{q,j} \right| < \tau \qquad (12)$$

Obviously, the GENITOR model promotes elitism since in each generation, only the worst chromosomes are replaced by the offspring and the elite chromosomes are kept in the population.

5. Experimental Results

In this section, we firstly optimize the PWD weights by the proposed genetic algorithm (see Section 5.1). Then, the performance of the proposed W3C is compared with wavelet correlogram and SIMPLIcity (see Section 5.2). In the above simulation steps, a subset of COREL[1] database with 1000 images is used as the non-medical reference imagebase $\mathbf{A}'$ ($|\mathbf{A}'| = 1000$). The images in this reference imagebase were categorized in 10 categories (each category includes 100 images) as listed in Table (1). A retrieved image has been considered a match if it belongs to the same category of the query image.

Finally, W3C is implemented for medical image indexing and retrieval (see Section 5.3) utilizing a medical imagebase. This medical reference imagebase ($\mathbf{A}''$) includes 1030 ($|\mathbf{A}''| = 1030$) CT-Scan images from 30 different patients. The images are gotten from different organs such as chest, neck, head, knee, and so fourth. In the imagebase, two images will be considered similar, if they are gotten from similar slices.

[1] From SIMPLIcity site: http://wang.ist.psu.edu/docs/related/

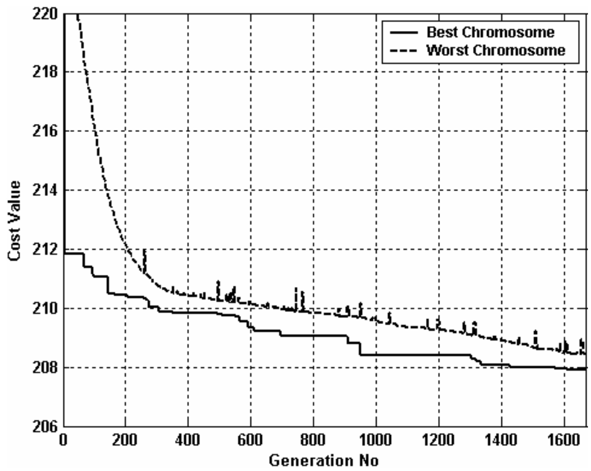

Fig. 3. Variations of evaluation value for the best and worst chromosomes during evolution of the proposed genetic algorithm to optimize PWD weights for W3C.

5.1 Optimizing PWD Weighting Coefficients

The PWD weighting coefficients are optimized by the proposed genetic algorithm. The parameters K_{GA}, K_{Tour}, P_{m}, τ, and μ was experimentally set to 150, 30, 0.002, 2.0, and 1, respectively.

Fig. 3 shows the variations of evaluation value for the best and worst chromosomes during evolution. The proposed genetic algorithm could reliably reduce the evaluation (cost) value of the best chromosome from 220 to 208 (equal to 5.8%) during evolution.

5.2 Comparing Performances

The performance of the proposed method is compared with wavelet correlogram [13] and SIMPLIcity [11] algorithm using average rank and average recall measures. The recall measure for the query image $\mathbf{I}_k$ ($k = 1,2,\ldots,|\mathbf{A}|$) is defined as follows,

$$R(\mathbf{I}_k;\mathbf{C}_{\text{opt}}) = \frac{\left|\left\{ j \middle| Rank(\mathbf{I}_j;\mathbf{I}_k,\mathbf{C}_{\text{opt}}) < |\mathbf{A}_k|,\ j \in \mathbf{A}_k \right\}\right|}{|\mathbf{A}_k|} \qquad (13)$$

The average rank and average recall for the images belonging to the q^{th} category ($\hat{\mathbf{A}}_q$) have been computed by the following equations, respectively:

$$\overline{\Gamma}_q(\mathbf{C}_{\text{opt}}) = \sum_{k \in \hat{\mathbf{A}}_q} \frac{\Gamma(\mathbf{I}_k, \mathbf{C}_{\text{opt}})}{|\hat{\mathbf{A}}_q|}, \qquad q = 1,2,\ldots,10 \qquad (14)$$

Table 1. Comparing the performance of W3C, wavelet correlogram, and SIMPLIcity in terms of both average precision and rank.

		SIMPLIcity		Wavelet Correlogram		W3C	
	Category	$\overline{R}$ (%)	$\overline{C}$	$\overline{R}$ (%)	$\overline{C}$	$\overline{R}$ (%)	$\overline{C}$
1	**Africans**	47.4	178	29.5	288	38.5	229
2	**Beaches**	32.3	241	28.9	341	31.1	297
3	**Buildings**	32.9	261	29.3	316	29.5	290
4	**Buses**	36.2	260	62.7	113	68.3	91
5	**Dinosaurs**	97.9	50	26.2	421	72.9	135
6	**Elephants**	40.0	196	30.9	241	43.0	177
7	**Flowers**	40.0	298	58.6	150	66.7	107
8	**Horses**	71.6	92	36.7	267	38.9	246
9	**Mountains**	34.2	230	23.0	335	27.2	285
10	**Food**	33.7	271	34.7	242	36.9	223
	Total	46.6	208	36.1	271	45.3	208

Tabel 2. The performance of the proposed W3C algorithm for 30 different medical query images. In the table, QII is the abbreviation of the term “query image index”.

QII	η (%)	**QII**	η (%)	**QII**	η (%)	**QII**	η (%)	**QII**	η (%)
0	100%	182	66.6%	394	100%	568	75%	852	58.3%
24	100%	203	100%	406	100%	578	100%	853	100%
51	66.6%	256	33.3%	415	100%	594	16.7%	900	25%
60	83.3%	298	50%	461	100%	603	25%	926	66.6%
125	58.3%	321	100%	492	100%	718	91.7%	955	83.3%
147	100%	380	100%	541	100%	841	83.3%	999	41.7%
Total		**77.5%**							

$$\overline{R}_q(\mathbf{C}_{\text{opt}}) = \sum_{k\in\hat{\mathbf{A}}_q} \frac{R(\mathbf{I}_k,\mathbf{C}_{\text{opt}})}{\left|\hat{\mathbf{A}}_q\right|}, \qquad q = 1,2,\ldots,10 \tag{15}$$

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

$$\overline{\Gamma} = \overline{\Gamma}(\mathbf{C}_{\text{opt}}) = \sum_{k\in\mathbf{A}} \frac{\Gamma(\mathbf{I}_k,\mathbf{C}_{\text{opt}})}{|\mathbf{A}|} \tag{16}$$

$$\overline{R} = \sum_{k\in\mathbf{A}} \frac{R(\mathbf{I}_k,\mathbf{C}_{\text{opt}})}{|\mathbf{A}|} \tag{17}$$

Table (1) compares the performance of W3C, wavelet correlogram, and SIMPLIcity. W3C makes 9.2% improvement over wavelet correlogram and only 1.3% deterioration under SIMPLIcity in terms of average precision. Furthermore, W3C provides better average rank compared to wavelet correlogram (by 63) and the same average rank as in SIMPLIcity. This is while; SIMPLIcity uses color information [11] in contrast to W3C that indexes gray-level images. Fig. 4 illustrates two query results of W3C for the non-medical imagebase. In each query, the precision of the CBIR algorithm is appeared at the right-hand side of the GUI.

5.3 Implementation for a Medical Imagebase

The proposed method is implemented for the medical reference imagebase. Tabel 2 shows the performance of the proposed W3C for 30 different randomly-seleceted medical query images based on effectiveness measure (with N equal to 12) [19]. For query image $\mathbf{I}_k$, the effectiveness is defined as follows,

$$\eta(\mathbf{I}_k;\mathbf{C}_{\text{opt}}) = \begin{cases} P(\mathbf{I}_k;\mathbf{C}_{\text{opt}}) & N < |\mathbf{A}_k| \\ R(\mathbf{I}_k;\mathbf{C}_{\text{opt}}) & \text{Otherwise} \end{cases} \tag{18}$$

where, the precision $P(\mathbf{I}_k;\mathbf{C}_{\text{opt}})$ is given by,

$$P(\mathbf{I}_k;\mathbf{C}_{\text{opt}}) = \frac{\left|\left\{ j \middle| Rank(\mathbf{I}_j;\mathbf{I}_k,\mathbf{C}_{\text{opt}}) < N,\ j\in\mathbf{A}_k \right\}\right|}{N} \tag{19}$$

The effectiveness measure is suitable when the number of relevant images in the reference imagebase is smaller than N for some query images [19] (like in the medical reference imagebase). The effectiveness of W3C is significant as 77.5% for the medical reference imagebase. Therefore, W3C is a suitable method for indexing and retrieval of medical images as well as non-medical ones. Fig. 5 illustrates two query results of W3C for the medical imagebase.

6. Conclusion

In this paper, a new method called W3C in CBIR was presented. W3C extends the wavelet correlogram method by including a CCV feature computed for low frequency wavelet coefficients to take into consideration texture information. Additionally, a new distance measure that is optimized by genetic algorithms is utilized in the retrieval algorithm of the above proposed method. Simulation results demonstrated good performance for the proposed CBIR algorithm.

In future, the index vector length will be reduced and it will be expanded to include shape information in the other directions in addition to the current vertical and horizontal directions.

References

[1] "Special issue on digital libraries," *IEEE Trans. Pattern Anal. Mach. Intell.,* vol. 18, no. 8, 1996.

[2] A. W. M. Smeulders, M. Worring, S. Santini, A. Gupta, and R. Jain, "Content-based image retrieval at the end of early years," *IEEE Trans. Pattern Anal. Mach. Intell.,* vol. 22, no. 12, pp. 1340-1380, 2000.

[3] V.N. Gudivada and V.V. Raghavan, "Content based image retrieval systems," *IEEE Computer*, vol. 28, no. 9, pp. 18-22, 1995.

[4] A. Del Bimbo, M. Mugnaini, P. Pala, and F. Turco, "Visual querying by color perceptive regions," *Pattern Recognition*, vol. 31, no. 9, pp. 1241-1253, 1998.

[5] G. Pass, R. Zabih, J. Miller, "Comparing images using color coherence vectors," *Proc. 4th ACM Multimedia Conf.*, 1996.

[6] J. Huang, S. Ravi Kumar, M. Mitra, W.J. Zhu, and R. Zabih, "Image indexing using color correlograms," in *Proc. IEEE Computer Soc. Conf. Computer Vision and Pattern Recognit.*, pp. 762-768, 1997.

[7] M. Stricker and A. Dimai, "Spectral covariance and fuzzy regions for image indexing," *Machine Vision Applications*, vol. 10, no. 2, pp. 66-73, 1997.

[8] F. Mahmoudi, J. Shanbehzadeh, A.M. Eftekhari-Moghadam, and H. Soltanian-Zadeh, "Image retrieval based on shape similarity by edge orientation autocorrelogram," *Pattern Recognit.*, vol. 36, no. 8, pp. 1725-1736, 2003.

[9] R. Schettini, G. Ciocca, and S. Zuffi, "A survey on methods for color image indexing and retrieval in image databases," *Color Imaging Science: Exploiting Digital Media,* R. Luo and L. MacDonald eds., J. Wiley, 2001.

[10] L. Balmelli and A. Mojsilovic, "Wavelet domain features for texture description, classification and replicability analysis", in *Wavelets in Signal and Image Analysis: from Theory to Practice* (edited book), Netherland: Kluwer Academic Publishers, 2001.

[11] J.Z. Wang, J. Li, and G. Wiederhold, "SIMPLIcity: semantics-sensitive integrated matching for picture libraries," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 23, no. 9, pp. 947-963, 2001.

[12] H. Abrishami Moghadam, T. Taghizadeh Khajoie, A.H. Rouhi, and M. Saadatmand-T., "Wavelet correlogram: a new approach for image indexing and retrieval," *Pattern Recognit.*, vol. 38, no. 12, Dec. 2005.

[13] H. Abrishami Moghadam, T. Taghizadeh Khajoie, A.H. Rouhi, "A new algorithm for image indexing and retrieval using wavelet correlogram," in *Proc. IEEE Int'l Conf. Image Process.*, vol. 2, pp. 497-500, 2003.

[14] M. Saadatmand-Tarzjan, H. Abrishami Moghadam, "A novel evolutionary approach for optimizing content-based image indexing algorithms," Revised for publication in *IEEE Trans. Systems, Man, and Cybernetics-Part B: Cybernetics*, 2005.

[15] D. Whitley, "A genetic algorithm tutorial," *Statistics and Computing*, vol. 4, no. 2, pp. 65-85, 1994.

[16] M. A. Lee and H. Takagi, "Embedding apriori knowledge into an integrated fuzzy system design method based on genetic algorithm," in *Proc. 5th IFSA World Congress*, 1993.

[17] C. Darwin, *The origin of species by means of natural selection*, Murray, 1859.

[18] D. Whitley, “The GENITOR algorithm and selective pressure”, in *Proc. 3rd Int’l Conf. Genetic Algorithms*, ed. Morgan-Kaufmann, pp. 116-121, 1989.

[19] B.M. Mehtre, M.S. Kankanhalli, A. Desai Narasimhalu, G.C. Man, “Color matching for image retrieval,” *Pattern Recognition Letters*, 16:325-331, 1995.

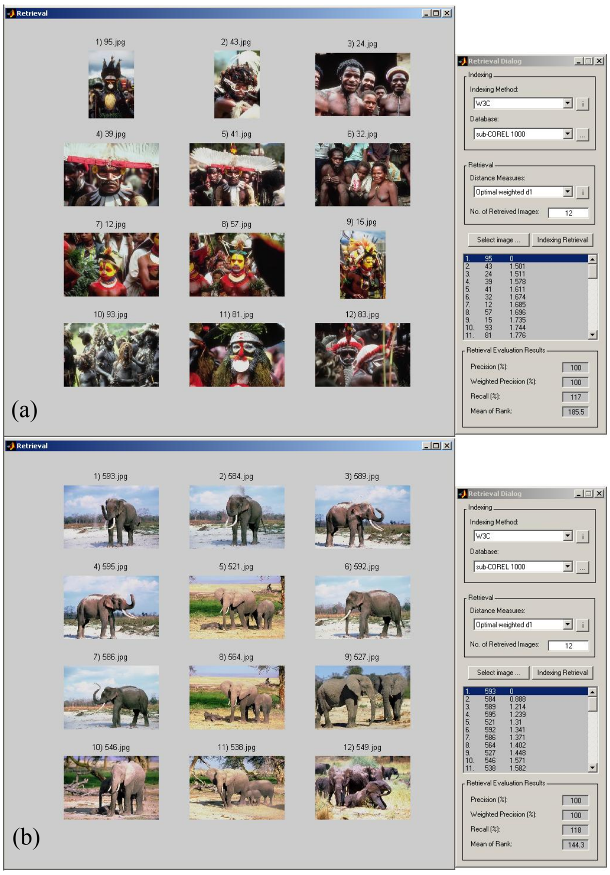

Fig 4. The W3C solutions for two non-medical query images including (a) 95, (b) 593. The precision of the algorithm is appeared at the right-hand side of the GUI.

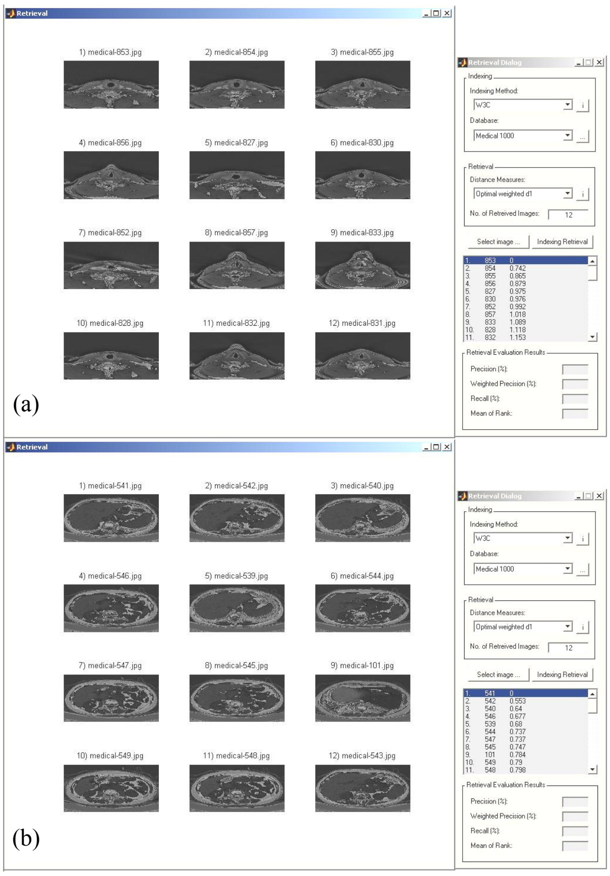

Fig 5. The W3C solutions for two medical query images including (a) 541, (b) 853. The precision of the algorithm is appeared in Tabel 2.