Content Based Image Retrieval using Color and Texture

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ABSTRACT

The increased need of content based image retrieval technique can be found in a number of different domains such as Data Mining, Education, Medical Imaging, Crime Prevention, Weather forecasting, Remote Sensing and Management of Earth Resources. This paper presents the content based image retrieval, using features like texture and color, called WBCHIR (Wavelet Based Color Histogram Image Retrieval).The texture and color features are extracted through wavelet transformation and color histogram and the combination of these features is robust to scaling and translation of objects in an image. The proposed system has demonstrated a promising and faster retrieval method on a WANG image database containing 1000 general-purpose color images. The performance has been evaluated by comparing with the existing systems in the literature.

Keywords

Image Retrieval, Color Histogram, Color Spaces, Quantization, Similarity Matching, Haar Wavelet, Precision and Recall.

1. INTRODUCTION

Research on content-based image retrieval has gained tremendous momentum during the last decade. A lot of research work has been carried out on Image Retrieval by many researchers, expanding in both depth and breadth [1]-[5]. The term Content Based Image Retrieval (CBIR) seems to have originated with the work of Kato [6] for the automatic retrieval of the images from a database, based on the color and shape present. Since then, the term has widely been used to describe the process of retrieving desired images from a large collection of database, on the basis of syntactical image features (color, texture and shape). The techniques, tools and algorithms that are used, originate from the fields, such as statistics, pattern recognition, signal processing, data mining and computer vision. In the past decade, many image retrieval systems have been successfully developed, such as the IBM QBIC System [7], developed at the IBM Almaden Research Center, the VIRAGE System [8], developed by the Virage Incorporation, the Photobook System [9], developed by the MIT Media Lab, the VisualSeek System [10], developed at Columbia University, the WBIIS System [11] developed at Stanford University, and the Blobworld System [12], developed at U.C. Berkeley and SIMPLIcity System [13]. Since simply color, texture and shape features cannot sufficiently represent image semantics, semantic-based image retrieval is still an open problem. CBIR is the most important and effective image retrieval method and widely studied in both academia and industry arena. In this paper we propose an image retrieval system, called Wavelet-Based Color Histogram Image Retrieval (WBCHIR), based on the combination of color and texture features.The color histogram for color feature and wavelet representation for texture and location information of an image. This reduces the processing time for retrieval of an image with more promising representatives. The extraction of color features from digital images depends on an understanding of the theory of color and the representation of color in digital images. Color spaces are an important component for relating color to its representation in digital form. The transformations between different color spaces and the quantization of color information are primary determinants of a given feature extraction method. Color is usually represented by color histogram, color correlogram, color coherence vector and color moment, under certain a color space [14-17]. The color histogram feature has been used by many researchers for image retrieval [18 and 19]. A color histogram is a vector, where each element represents the number of pixels falling in a bin, of an image [20]. The color histogram has been used as one of the feature extraction attributes with the advantage like robustness with respect to geometric changes of the objects in the image. However the color histogram may fail when the texture feature is dominant in an image [21]. Li and Lee [22] have proposed a ring based fuzzy histogram feature to overcome the limitation of conventional color histogram. The distance formula used by many researchers, for image retrieval, include Histogram Euclidean Distance, Histogram Intersection Distance, Histogram Manhattan Distance and Histogram Quadratic Distance [23-27].

Texture is also considered as one of the feature extraction attributes by many researchers [28-31]. Although there is no formal definition for texture, intuitively this descriptor provides measures of the properties such as smoothness, coarseness, and regularity. Mainly the texture features of an image are analyzed through statistical, structural and spectral methods [32].

The rest of the paper is organized as follows: In section 2, a brief review of the related work is presented. The section 3 describes the color feature extraction. The section 4, presents the texture feature extraction and the section 5, presents the similarity matching. The proposed method is given in section 6 and section 7 describes the performance evaluation of the proposed method. Finally the experimental work and the conclusions are presented in section 8 and section 9 respectively.

2. RELATED WORK

Lin et al. [14] proposed a color-texture and color-histogram based image retrieval system (CTCHIR). They proposed (1) three image features, based on color, texture and color distribution, as color co-occurrence matrix (CCM), difference between pixels of scan pattern (DBPSP) and color histogram for K-mean (CHKM) respectively and (2) a method for image retrieval by integrating CCM, DBPSP and CHKM to enhance image detection rate and simplify computation of image retrieval. From the experimental results they found that, their proposed method outperforms the Jhanwar et al. [33] and Hung and Dai [34] methods. Raghupathi et al. [35] have made a comparative study on image retrieval techniques, using different feature extraction methods like color histogram, Gabor Transform, color histogram+gabour transform, Contourlet Transform and color histogram+contourlet transform. Hiremath and Pujari [36] proposed CBIR system based on the color, texture and shape features by partitioning the image into tiles. The features computed on tiles serve as local descriptors of color and texture features. The color and texture analysis are analyzed by using two level grid frameworks and the shape feature is used by using Gradient Vector Flow. The comparison of experimental result of proposed method with other system [37]-[40] found that, their proposed retrieval system gives better performance than the others. Rao et al. [41] proposed CTDCIRS (color-texture and dominant color based image retrieval system), they integrated three features like Motif co-occurrence matrix (MCM) and difference between pixels of scan pattern (DBPSP) which describes the texture features and dynamic dominant color (DDC) to extract color feature. They compared their results with the work of Jhanwar et al. [33] and Hung and Dai [34] and found that their method gives better retrieval results than others.

3. COLOR FEATURE

The color feature has widely been used in CBIR systems, because of its easy and fast computation [42]-[43]. Color is also an intuitive feature and plays an important role in image matching. The extraction of color features from digital images depends on an understanding of the theory of color and the representation of color in digital images. The color histogram is one of the most commonly used color feature representation in image retrieval. The original idea to use histogram for retrieval comes from Swain and Ballard [27], who realized the power to identify an object using color is much larger than that of a gray scale.

3.1 COLOR SPACE SELECTION AND COLOR QUANTIZATION

The color of an image is represented, through any of the popular color spaces like RGB, XYZ, YIQ, L*a*b*, U*V*W*, YUV and HSV [44]. It has been reported that the HSV color space gives the best color histogram feature, among the different color spaces [45]-[49]. The application of the HSV color space in the content-based image retrieval has been reported by Surel et al. [50]. In HSV color space the color is presented in terms of three components: Hue (H), Saturation (S) and Value (V) and the HSV color space is based on cylinder coordinates [51 and 52].

Color quantization is a process that optimizes the use of distinct colors in an image without affecting the visual properties of an image. For a true color image, the distinct number of colors is up to $2^{24} = 16777216$ and the direct extraction of color feature from the true color will lead to a large computation. In order to reduce the computation, the color quantization can be used to represent the image, without a significant reduction in image quality, thereby reducing the storage space and enhancing the process speed [53]. The effect of color quantization on the performance of image retrieval has been reported by many authors [53 and 54].

3.2 Color Histogram

A color histogram represents the distribution of colors in an image, through a set of bins, where each histogram bin corresponds to a color in the quantized color space. A color histogram for a given image is represented by a vector:

$$\mathrm{H} = \{\mathrm{H}[0], \mathrm{H}[1], \mathrm{H}[2], \mathrm{H}[3], \ldots\ldots\ldots\ldots \mathrm{H}[\mathrm{i}], \ldots\ldots\ldots, \mathrm{H}[\mathrm{n}]\}$$

Where i is the color bin in the color histogram and H[i] represents the number of pixels of color i in the image, and n is the total number of bins used in color histogram. Typically, each pixel in an image will be assigned to a bin of a color histogram. Accordingly in the color histogram of an image, the value of each bin gives the number of pixels that has the same corresponding color. In order to compare images of different sizes, color histograms should be normalized. The normalized color histogram H' is given as:

$$\mathrm{H}' = \{\mathrm{H}'[0], \mathrm{H}'[1], \mathrm{H}'[2], \ldots\ldots, \mathrm{H}'[\mathrm{i}], \ldots., \mathrm{H}'[\mathrm{n}]\}$$

Where $\mathrm{H}'[\mathrm{i}] = \frac{\mathrm{H}[\mathrm{i}]}{\mathrm{P}}$, p is the total number of pixels of an image [55].

4. TEXTURE FEATURE

Like color, the texture is a powerful low-level feature for image search and retrieval applications. Much work has been done on texture analysis, classification, and segmentation for the last four decade, still there is a lot of potential for the research. So far, there is no unique definition for texture; however, an encapsulating scientific definition as given in [56] can be stated as, “Texture is an attribute representing the spatial arrangement of the grey levels of the pixels in a region or image”. The common known texture descriptors are Wavelet Transform [57], Gabor-filter [58], co-occurrence matrices [59] and Tamura features [60]. We have used Wavelet Transform, which decomposes an image into orthogonal components, because of its better localization and computationally inexpensive properties [30 and 31].

4.1 Haar Discrete Wavelet Transforms

Discrete wavelet transformation (DWT) [61] is used to transform an image from spatial domain into frequency domain. The wavelet transform represents a function as a superposition of a family of basis functions called wavelets. Wavelet transforms extract information from signal at different scales by passing the signal through low pass and high pass filters. Wavelets provide multi-resolution capability and good energy compaction. Wavelets are robust with respect to color intensity shifts and can capture both texture and shape information efficiently. The wavelet transforms can be computed linearly with time and thus allowing for very fast algorithms [28].
DWT decomposes a signal into a set of Basis Functions and Wavelet Functions. The wavelet transform computation of a two-dimensional image is also a multi-resolution approach, which applies recursive filtering and sub-sampling. At each level (scale), the image is decomposed into four frequency sub-bands, LL, LH, HL, and HH where L denotes low frequency and H denotes high frequency as shown in Figure1.

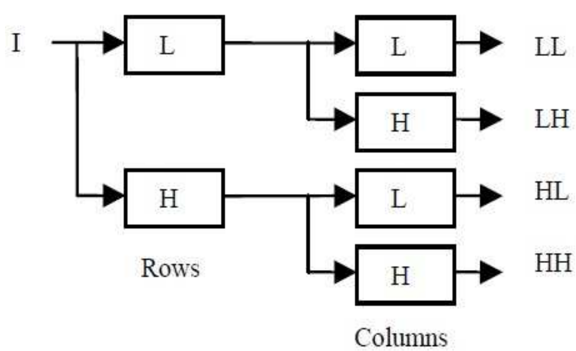

Figure 1. Discrete Wavelet Sub-band Decomposition

Haar wavelets are widely being used since its invention after by Haar [62]. Haar used these functions to give an example of a countable orthonormal system for the space of square-integrable functions on the real line. In this paper, we have used Haar wavelets to compute feature signatures, because they are the fastest to compute and also have been found to perform well in practice [63]. Haar wavelets enable us to speed up the wavelet computation phase for thousands of sliding windows of varying sizes in an image. The Haar wavelet's mother wavelet function ψ(t) can be described as:

$$\psi(t) = \begin{cases} 1\,, 0 \le t \le \frac{1}{2} \\ -1\,, \frac{1}{2} \le t < 1 \\ 0\,, \text{otherwise} \end{cases} \tag{1}$$

and its scaling function φ(t) can be described as:

$$\varphi(t) = \begin{cases} 1, 0 \leq t < 1 \\ 0, \text{otherwise} \end{cases} \quad (2)$$

5. FEATURE SIMILARITY MATCHING

The Similarity matching is the process of approximating a solution, based on the computation of a similarity function between a pair of images, and the result is a set of likely values. Exactness, however, is a precise concept. Many researchers have used different similarity matching techniques [23]-[27]. In our study, we have used the Histogram Intersection Distance method, for the reasons given in [64].

5.1 Histogram Intersection Distance:

Swain and Ballard [27] proposed histogram intersection for color image retrieval. Intersection of histograms was originally defined as:

$$d_{ID} = \frac{\sum_{i=1}^{i=n} \min\left[Q[i],\ \ D[i]\right]}{[|\ D[i]|]} \quad (3)$$

Smith and Chang [55] extended the idea, by modifying the denominator of the original definition, to include the case when the cardinalities of the two histograms are different and expressed as:

$$d_{ID} \frac{\sum_{i=1}^{i=n} \min[Q[i],\ \ D[i]]}{\min[|Q[i]|, D[i]]} \quad (4)$$

and |Q| and |D| represents the magnitude of the histogram for query image and a representative image in the Database.

6. PROPOSED METHOD

In this study we are proposing two algorithms for image retrieval based on the color histogram and Wavelet-based Color Histogram. The block diagrams of the proposed methods are shown in Figure 2. and Figure 3.

6.1. Color Histogram

Step 1. Convert RGB color space image into HSV color space.
Step 2. Color quantization is carried out using color histogram by assigning 8 level each to hue, saturation and value to give a quantized HSV space with 8x8x8=512 histogram bins.
Step 3. The normalized histogram is obtained by dividing with the total number of pixels.
Step 4. Repeat step1 to step3 on an image in the database.
Step 5. Calculate the similarity matrix of query image and the image present in the database.
Step 6. Repeat the steps from 4 to 5 for all the images in the database.
Step 7. Retrieve the images.

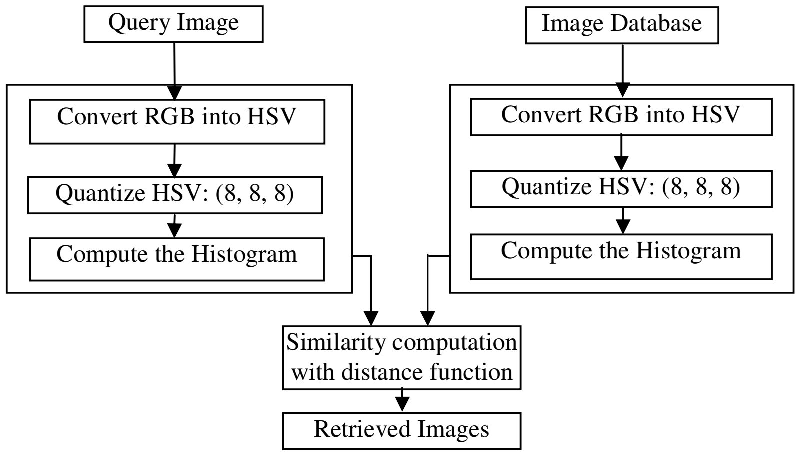

Figure 2. Block diagram of proposed Color Histogram

6.2. Wavelet-Based Color Histogram (WBCH).

Step1. Extract the Red, Green, and Blue Components from an image.

Step2. Decompose each Red, Green, Blue Component using Haar Wavelet transformation at 1st level to get approximate coefficient and vertical, horizontal and diagonal detail coefficients.

Step3. Combine approximate coefficient of Red, Green, and Blue Component.

Step4. Similarly combine the horizontal and vertical coefficients of Red, Green, and Blue Component.

Step5. Assign the weights 0.003 to approximate coefficients, 0.001 to horizontal and 0.001 to vertical coefficients (experimentally observed values).

Step6. Convert the approximate, horizontal and vertical coefficients into HSV plane.

Step7. Color quantization is carried out using color histogram by assigning 8 level each to hue, saturation and value to give a quantized HSV space with 8x8x8=512 histogram bins.

Step8. The normalized histogram is obtained by dividing with the total number of pixels.

Step9. Repeat step1 to step8 on an image in the database.

Step10. Calculate the similarity matrix of query image and the image present in the database.

Step11. Repeat the steps from 9 to 10 for all the images in the database.

Step12. Retrieve the images.

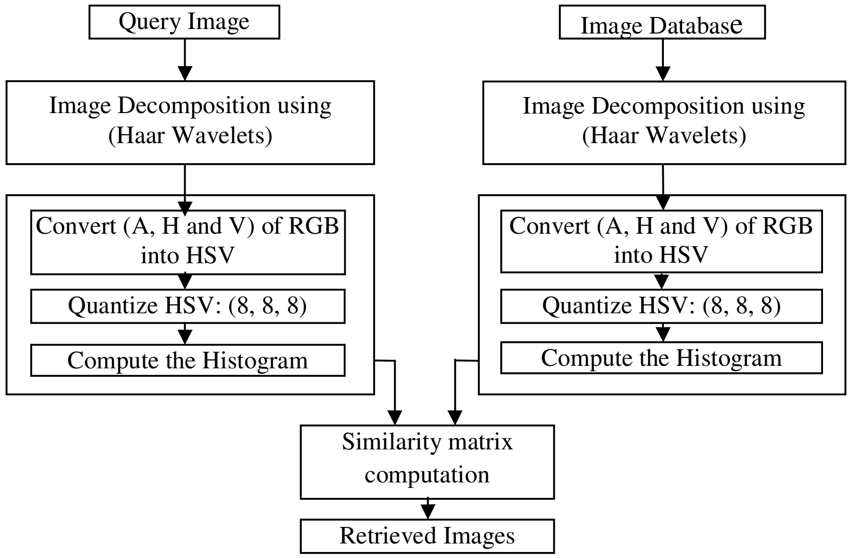

Figure 3. Block diagram of proposed Wavelet-Based Color Histogram (WBCH). (A-approximate coefficient, H-horizontal detail coefficient, V-vertical detail coefficient).

7. PERFORMANCE EVALUATION

The performance of retrieval of the system can be measured in terms of its recall and precision. Recall measures the ability of the system to retrieve all the models that are relevant, while precision measures the ability of the system to retrieve only the models that are relevant. It has been reported that the histogram gives the best performance through recall and precision value [35, 44]. They are defined as:

$$\text{Precision} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of images retrieved}} = \frac{\text{A}}{\text{A+B}} \tag{5}$$

$$\text{Recall} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of relevant images}} = \frac{\text{A}}{\text{A+C}} \tag{6}$$

Where A represent the number of relevant images that are retrieved, B, the number of irrelevant items and the C, number of relevant items those were not retrieved. The number of relevant items retrieved is the number of the returned images that are similar to the query image in this case. The total number of items retrieved is the number of images that are returned by the search engine.

The average precision for the images that belongs to the q^{th} category (A_q) has been computed by [65]

$$p' = \sum_{k \in A_q} \frac{p(i_k)}{|A_q|} \tag{7}$$

Where q=1, 2……10.
Finally, the average precision is given by:

$$p' = \sum_{q=1}^{10} p'_q / 10. \tag{8}$$

8. EXPERIMENT

The proposed method has been implemented using Matlab 7.3 and tested on a general-purpose WANG database [66] containing 1,000 images of the Corel stock photo, in JPEG format of size 384x256 and 256x386 as shown in Figure 4. The search is usually based on similarity rather than the exact match. We have followed the image retrieval technique, as described in the section 6.1 on different quantization schemes. The quality of the image retrieval, with different quantization schemes like (4, 4, 4), (4, 8, 8), (8, 4, 4), (8, 8, 4), (8, 8, 8), (16, 4, 4) and (18, 3, 3) has been evaluated by randomly selecting 10 query images, of each category, from the image database. Each query returns the top 10 images from database, and the calculated precision values, using the equation 5, and average precision using equation 8 are given in the Table 1. The average precision (7.8) value of (8, 8, 8) quantization bin indicates the better retrieval results than the others.

Table 1. Precision Using Different Quantization Schemes

Category	**4,4,4**	**4,4,8**	**4,8,8**	**8,4,4**	**8,8,4**	**8,8,8**	**16,4,4**	**18,3,3**
African People	9	9	9	9	9	9	10	9
Beach	6	5	5	4	6	6	3	5
Building	6	6	6	6	7	6	8	9
Buses	9	9	9	9	9	9	9	8
Dinosaurs	8	10	9	7	8	9	8	8
Elephants	7	8	8	7	8	9	7	7
Flowers	6	6	6	7	7	7	7	6
Horses	9	9	9	10	9	9	10	10
Mountains	6	6	6	5	5	6	6	5
Food	8	7	9	8	8	8	8	8
Average precision	7.4	7.5	7.6	7.2	7.6	7.8	7.6	7.5

The WBCH method, as discussed in section 6.2, has been used to study the image retrieval using (8,8,8) color quantization bin and the performance of the proposed image retrieval technique has been evaluated by comparing the results with the results of different authors [14, 35, 36 and 41] as shown in the Table 2. The effectiveness of the WBCH retrieval method is evaluated by selecting 10 query images under each category of different semantics. For each query, we examined the precision of the retrieval, based on the relevance of the image semantics. The semantic relevance is determined by manual truthing the query image and each of the retrieved images in the retrieval. The precision values, calculated by using the equation 5 and also the average precision using the equation 8 are shown in Table 2. The 10 query retrievals by the proposed method are shown in Figures 5-14, with an average retrieval time as 1min. These results clearly show that the performance of the proposed method is better than the other methods.

Table 2: Precision of the Retrieval by different methods

Classes	**Category**	**WBCH**	**CH**	**[14]**	**[35]**	**[36]**	**[41]**
1	African people	0.65	0.72	0.68	0.75	0.54	0.562
2	Beach	0.62	0.53	0.54	0.6	0.38	0.536
3	Building	0.71	0.61	0.56	0.43	0.30	0.61
4	Buses	0.92	0.93	0.89	0.69	0.64	0.893
5	Dinosaurs	0.97	0.95	0.99	1	0.96	0.984
6	Elephants	0.86	0.84	0.66	0.72	0.62	0.578
7	Flowers	0.76	0.66	0.89	0.93	0.68	0.899
8	Horses	0.87	0.89	0.8	0.91	0.75	0.78
9	Mountains	0.49	0.47	0.52	0.36	0.45	0.512
10	Food	0.77	0.82	0.73	0.65	0.53	0.694
	Average Precision	0.762	0.742	0.726	0.704	0.585	0.7048

Figure 4. Sample of WANG Image Database

Figure 5. Retrieve results for African People

Figure 6. Retrieve results for Beach

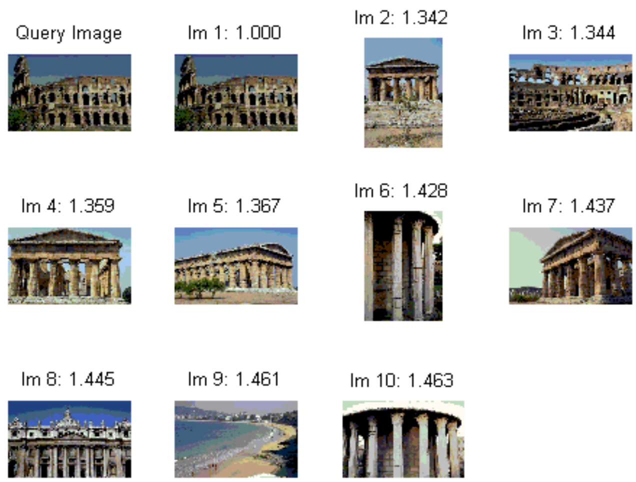

Figure 7. Retrieve results for Building

Figure 8. Retrieve results for Bus

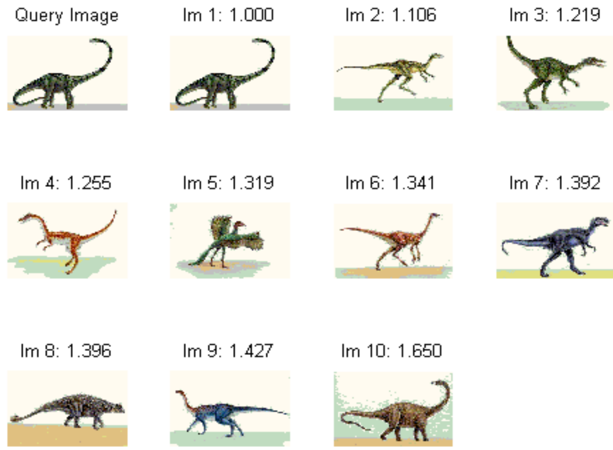

Figure 9. Retrieve results for Dinosaurs

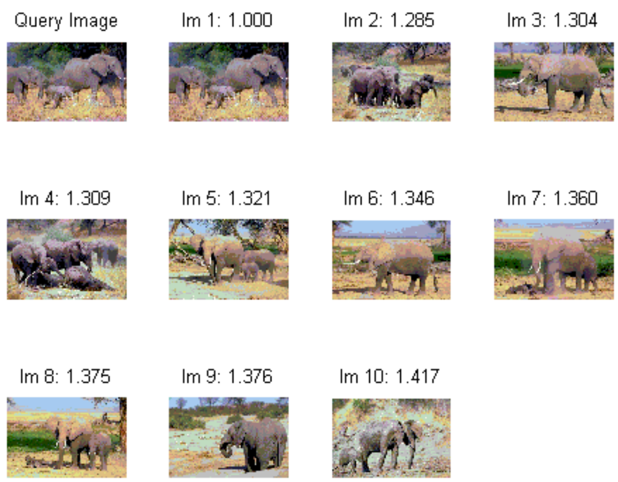

Figure 10. Retrieve results for Elephants

Figure 11. Retrieve results for Flowers

Figure 12. Retrieve results for Horses

Figure 13. Retrieve results for Mountains

Figure 14. Retrieve results for Food

9. CONCLUSION

In this paper, we presented a novel approach for Content Based Image Retrieval by combining the color and texture features called Wavelet-Based Color Histogram Image Retrieval (WBCHIR). Similarity between the images is ascertained by means of a distance function. The experimental result shows that the proposed method outperforms the other retrieval methods in terms of Average Precision. Moreover, the computational steps are effectively reduced with the use of Wavelet transformation. As a result, there is a substational increase in the retrieval speed. The whole indexing time for the 1000 image database takes 5-6 minutes.

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