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Image retrieval using histograms of uni-color and bi-color blocks and directional changes in intensity gradient ☆

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Abstract

In this paper, we present a new and effective image indexing technique that employs local uni-color and bi-color distributions and local directional distribution of intensity gradient. The image is divided into 4 by 4 non-overlapping blocks. Each block, based on its gradient magnitude, is classified as uniform or non-uniform. Using the average of each color component for the pixels of a uniform block, its representative color is found. Then the histogram of uni-color uniform blocks of the image, HUCUB, is constructed. To each non-uniform block, two representative colors are assigned. Then the histogram of bi-color non-uniform blocks, HBCNB, is created. To represent the shape content of the image, the histogram of directional changes in intensity gradient, HDCIG, is introduced. Experimental results on a database of 2250 images are reported.

Keywords: Content-based image retrieval; Image indexing; Color histogram; Intensity gradient

1. Introduction

In recent years, rapid advances in hardware technology and growth of computer power make facilities for storage and retrieval of huge amount of data in multimedia format. The need for content-based access to multimedia information has captured the interests of researchers. Image databases are now employed in diverse areas such as entertainment, art, fashion design, advertising, history, medicine and industry.

There are two different approaches in image retrieval: text-based and content-based. In both approaches, the key features are extracted from an image to index it. In the first approach, the indices of an image are extracted manually, while in the second, they are extracted automatically. When the size of image database is large, text-based image retrieval is faced with two difficulties (Rui and Huang, 1999). The first is the vast amount of labor required in manual image annotation and the

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other is the subjectivity of human perception that causes different annotation results for a particular image. Drawbacks of the text-based image indexing, speed up the research in content-based image retrieval, CBIR, where instead of keywords, the image is indexed by its visual content.

Content-based image retrieval systems operate in two phases: indexing and searching (Albanesi et al., 2001; Huang et al., 1997). In the indexing phase, for each image in the database, a feature vector capturing suitable attributes is computed and stored in a visual feature database. In the searching phase, when a user makes a query, a feature vector for that query is computed. Using a similarity criterion, this vector is compared to the vectors in the feature database. The images most similar to the query image are returned to the user.

A typical content-based image retrieval system is shown in Fig. 1. The image database contains images to be retrieved. The feature database stores the visual features extracted from these images. The retrieval system includes a graphical query interface for communicating to the user. It collects the required information from the user and displays the retrieval results to him. The query-processing module extracts suitable features from the query image. The similarity measurement module compares the query feature vector with the vectors of the feature database and finds the most similar images to the query image. In most image retrieval systems, there is a relevance feedback from the user, where human and computer can interact to improve the retrieval performance. The relevance feedback creates a powerful tool for the tuning of the similarity function parameters and introducing user subjectivity into the retrieval system.

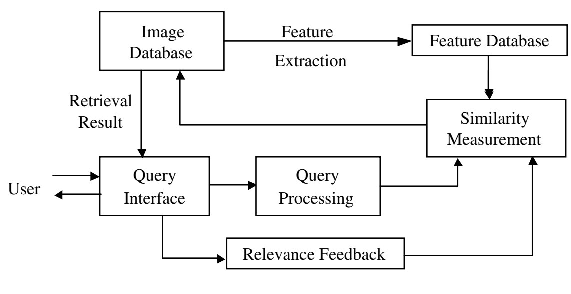

Fig. 1. A typical system for content-based image retrieval.

1.1. Related work

There are some literatures that survey the most important CBIR systems in both commercial and academic domains (Veitkamp and Tanase, 2000; Rui and Huang, 1999). Also there are some papers that overview and compare the current techniques in this area (Rui and Huang, 1999; Li et al., 2001; Antani et al., 2002; Marsicoi et al., 1997; Smeulders et al., 2000; Zhou and Huang, 2002; Lecce and Guerriero, 1999). In a CBIR system, each image is indexed by its visual features such as color, texture, shape and color layout. Since the early studies on CBIR, color features have been commonly used (Swain and Ballard, 1991; Jain and Vailaya, 1996). Swain and Ballard (1991) introduced the color histogram. A color histogram describes the global color distribution in an image. It is easy to compute and insensitive to small changes in viewing positions. However, the texture, shape and color layout information of an image are not shown in its color histogram. This causes the false positives to increase (Huang et al., 1997). This is especially critical in large image databases, where many images have almost the same color histogram.

Recently, several approaches have incorporated texture, shape and color layout information with color histogram to overcome its weakness (Smith and Li, 1999; Kim et al., 1997; Liu et al., 2000; Wang et al., 2001; Ravishkar et al., 1999; Qiu, 2001). One way is to divide the image into different regions and calculate color features for each region (Yoo et al., 2002a,b; Malki et al., 1999; Oja et al., 2000). Huang et al. (1997) proposed the color correlogram for image indexing. A color correlogram of an image is a matrix indexed by color pairs, where the kth entry for (i, j) specifies the probability of finding a pixel of color i at the distance k from a pixel of color j. Since the computation of the color correlogram is very time consuming, the use of color autocorrelogram is recommended which is a vector that only includes the diagonal entries of color correlogram matrix.

Mehtre et al. (1998) proposed a composite feature measure which combines the shape and color features of an image, based on a clustering technique. Pass and Zabih (1999) introduced a joint histogram which is a multi-dimensional histogram that incorporates additional information of local features such as edge density, texture and gradient magnitude into color histogram. Each entry in a joint histogram contains the number of pixels in the image that are described by a particular combination of feature values. Rao et al. (1999) generalized the color spatial distribution by computing the color histogram with specific geometric relationships between pixels of each color histogram bucket. Cinque et al. (2001) proposed a spatial-chromatic histogram in which the average position of each color and its standard deviation are extracted to include spatial information into the color histogram.

Malki et al. (1999) suggested a multi-resolution quad-tree approach for image indexing based on region queries without segmentation. In their method, color histograms are computed on sub-images of the quad-tree representation, yielding a high dimensional feature vector. Jain and Vailaya (1996) used color and shape features for image indexing. For color features, they applied three separate 1-D histograms in RGB color space. Each color axis is quantized to 16 levels. A histogram of the edge direction was also used to represent the shape attributes. Qiu (2002) suggested a model to represent achromatic and chromatic image signals. In YC_bC_r color space, each image is divided into 4 by 4 non-overlapping blocks. The blocks of Y sub-image are quantized to 256 levels to construct an achromatic histogram. The blocks of C_b and C_r sub-images, after a down sampling by a factor of 2 and combining, are also quantized to 256 levels, to create a chromatic histogram.

1.2. Our work

In this paper, we present a new indexing technique that employs local chromatic distribution and local directional distribution of intensity gradient (Nezamabadi-pour et al., 2003b,c). The image is divided into 4×4 non-overlapping blocks (Fig. 2). Each block, based on its intensity gradient, is classified to uniform or non-uniform. The non-uniform blocks are edgy blocks while the uniform blocks are homogeneous. To classify each block, its gradient magnitude is compared with a constant threshold. If it is greater than threshold, the block is identified as non-uniform, otherwise as uniform.

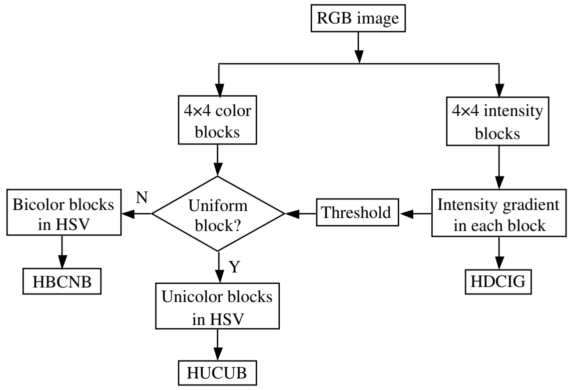

Fig. 2. Block diagram of the proposed indexing method. HBCNB: histogram of bi-color non-uniform blocks. HUCUB: histogram of uni-color uniform blocks. HDCIG: histogram of directional changes in intensity gradient.

For the pixels in each uniform block, the average of each color component is found to assign a representative color to that block. Then the histogram of uni-color uniform blocks of the image, HUCUB, is constructed.

For each non-uniform block, we find two representative colors. Then the histogram of bi-color non-uniform blocks of the image, HBCNB, is generated. Each entry (i, j) of HBCNB represents the number of blocks having colors i and j as their representative colors.

To represent the shape content of an image, the inter-block directional changes of the intensity gradient are counted and the histogram of directional changes in intensity gradient, HDCIG, is generated.

The rest of the paper is organized as follows. A short discussion on the use of HSV color space is presented in Section 2. Section 3 describes the proposed feature extraction and indexing method. Section 4 concerns with the experimental setup. The results obtained are presented in Section 5. Finally, a conclusion is given in Section 6.

2. Color space

The RGB space does not correspond to the human way of perceiving the colors and dose not separate the luminance component from the chrominance ones. We have used HSV color space, which is common for image retrieval systems (Albanesi et al., 2001; Smith and Li, 1999; Yoo et al., 2002a,b; Nezamabadi-pour et al., 2003a; Smith and Chang, 1996). In HSV space, the colors can be matched in a way that is fairly consistent with human perception (Albanesi et al., 2001; Yoo et al., 2002a). In this space, hue is used to distinguish colors, saturation is the percentage of white light added to a pure color and value refers to the perceived light intensity. The important advantages of HSV space are as follows (Plantaniotis and Venetsanopoulos, 2000): good compatibility with human intuition, separability of chromatic and achromatic components, and possibility of preferring one component to other.

Since the human visual system is more sensitive to hue than saturation and value, hue axis should be quantized into smaller intervals than saturation and value axes. In this work, we quantized HSV space into 6 uniform intervals for hue, 3 for saturation and 3 for value. This results in 54 bins for the color histogram.

3. Feature extraction and indexing

We denote an $m \times n$ color image by $\boldsymbol{C}$ and its pixels by $C(pq)$. Let $\boldsymbol{I}$ be the intensity image of $\boldsymbol{C}$. The disjoint 4×4 blocks of $\boldsymbol{I}$, as shown in Fig. 3a, are defined by Eq. (1).

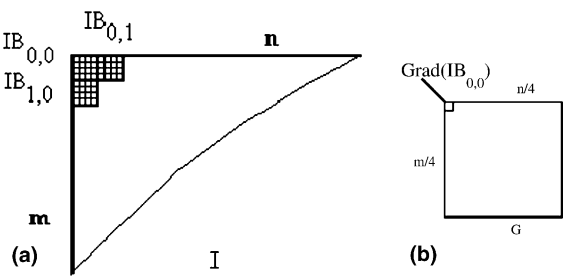

Fig. 3. (a) Intensity image $\boldsymbol{I}$ and three 4×4 intensity blocks and (b) gradient image $\boldsymbol{G}$.

$$\begin{aligned} \boldsymbol{IB}_{i,j} &= \{I(p,q) : 4i \leqslant p \leqslant 4i+3, 4j \leqslant q \leqslant 4j+3\}, \\ & i = 0,1,\ldots,(m/4)-1, \\ & j = 0,1,\ldots,(n/4)-1 \end{aligned} \tag{1}$$

Now, we make the gradient image $\boldsymbol{G}$ of the size $m/4$ by $n/4$ (Fig. 3b). Each entry of $\boldsymbol{G}$, defined by Eqs. (2)–(4), is the magnitude of the intensity gradient for the corresponding $\boldsymbol{IB}$ (Chen and Bovik, 1990).

$$\begin{aligned} \Delta_x \boldsymbol{IB}_{i,j} = {} & \mathrm{mean}\{I(p,q) : 4i+2 \leqslant p \leqslant 4i+3, \\ & 4j \leqslant q \leqslant 4j+3\} \\ & - \mathrm{mean}\{I(p,q) : 4i \leqslant p \leqslant 4i+1, \\ & 4j \leqslant q \leqslant 4j+3\} \end{aligned} \tag{2}$$

$$\begin{aligned} \Delta_y \boldsymbol{IB}_{i,j} = {} & \mathrm{mean}\{I(p,q) : 4i \leqslant p \leqslant 4i+3, \\ & 4j+2 \leqslant q \leqslant 4j+3\} \\ & - \mathrm{mean}\{I(p,q) : 4i \leqslant p \leqslant 4i+3, \\ & 4j \leqslant q \leqslant 4j+1\} \end{aligned} \tag{3}$$

$$G(i,j) = \sqrt{(\Delta_x IB_{i,j})^2 + (\Delta_y IBi,j)^2} \tag{4}$$

Two sample images and their corresponding gradient images are shown in Fig. 4.

3.1. Histogram of directional changes in intensity gradient, HDCIG

We introduce the histogram of directional changes in intensity gradient, HDCIG, to represent the shape content of the image (Fig. 2). This histogram is calculated for each quadrant of image $\boldsymbol{G}$, separately (Fig. 5a). A 3×3 window scans each quadrant (Fig. 5b). For each central pixel, every neighboring pixel is examined and the probability of that neighbor being brighter than the central pixel is calculated. This results in an 8-dimensional vector for each quadrant. These are concatenated to make a 32-dimensional shape vector for the entire image $\boldsymbol{G}$ (Fig. 6).

3.2. Histogram of uni-color uniform blocks, HUCUB

We apply a fixed threshold to the intensity gradient of each 4×4 block to classify it into uniform or non-uniform (Fig. 2). It has been

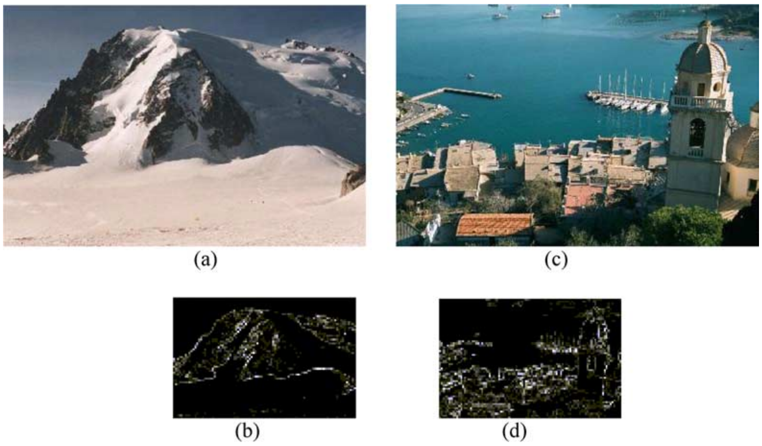

Fig. 4. (a) and (c) Two sample images; (b) and (d) corresponding gradient images.

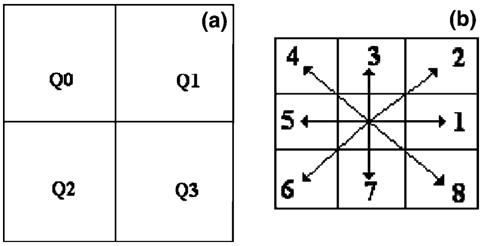

Fig. 5. (a) Four quadrants of $\boldsymbol{G}$, (b) the changes in intensity gradient are counted in 8 directions, separately.

shown that a good choice for the threshold is 13 (Chen and Bovik, 1990). If the gradient magnitude of a block is greater than 13, it is non-uniform, otherwise uniform.

For the pixels in each uniform block, the average of each RGB component is found to assign a representative color to that block. The representative colors are then transformed to HSV space and are quantized into $6 \times 3 \times 3 = 54$ colors. Finally the histogram of uni-color uniform blocks, HUCUB, is constructed. HUCUB is normalized by total number of image blocks. Fig. 7 shows the histograms of the images in Fig. 4.

3.3. Histogram of bi-color non-uniform blocks, HBCNB

Non-uniform blocks are edgy blocks. It is not reasonable to compute HUCUB for them. We, instead, assign two representative colors to each edgy block as follows. The average intensity of each block is found. The pixels brighter than the average are marked B, the others D. The average color for the B-pixels is calculated in the RGB space. This representative color is then transformed to HSV space and quantized into one of 54 predefined colors. The same is done to assign a representative color to the D-pixels. Then, we construct the histogram of bi-color non-uniform blocks, HBCNB. Each entry (i, j) of HBCNB represents the number of blocks having ith and jth colors as their representative colors. In a HBCNB the entry (i, j) is equal to the entry (j, i) and the entry (i, i) is zero. For a 54-quantization levels, HBCNB is of dimension $(54^2 - 54)/2 = 1431$. HBCNB is normalized by total number of image blocks. Fig. 8 shows the histograms of the images in Fig. 4. One sample of uniform blocks and two samples of non-uniform blocks and their B- and D-pixels are shown in Fig. 9.

4. Experimental setup

In our experiments, we used "query-by-example" method, QBE, where the user specifies an image, and the system tries to retrieve the most similar images from the database. As mentioned earlier, we quantized HSV space into 54 predefined colors, uniformly. When a user presents a

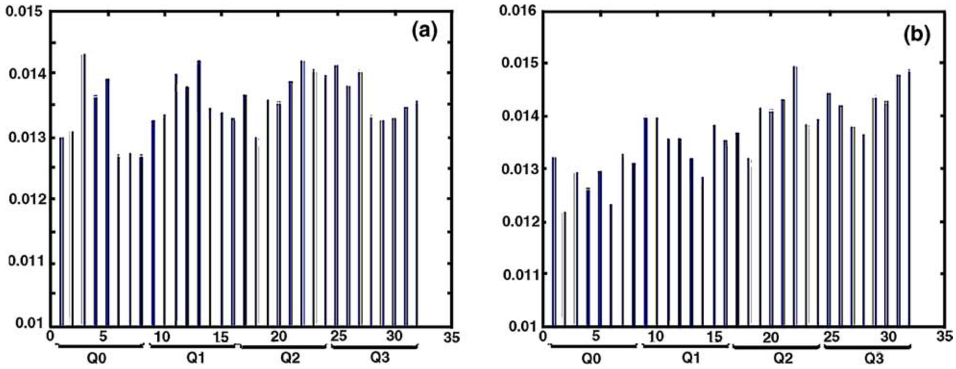

Fig. 6. (a) HDCIG of image in Fig. 4(a). (b) HDCIG of image in Fig. 4(c).

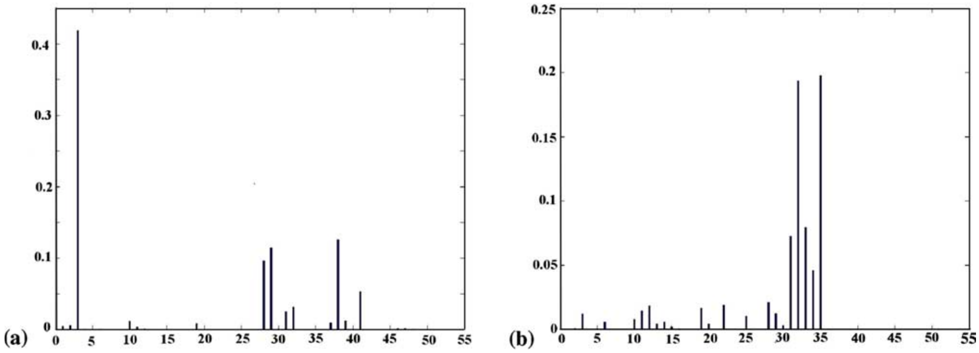

Fig. 7. (a) HUCUB of image in Fig. 4(a). (b) HUCUB of image in Fig. 4(c).

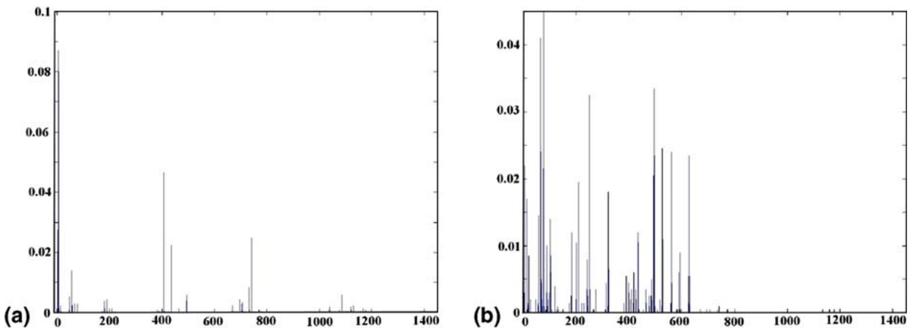

Fig. 8. (a) HBCNB of image in Fig. 4(a). (b) HBCNB of image in Fig. 4(c).

query image, its HDCIG, HUCUB and HBCNB are extracted. Then, the feature database is searched for the most similar images to the query image. All programs have been implemented in Matlab6.

4.1. Image database

Selecting a suitable database is a critical and important step in designing an image retrieval system. At the present time, there is not a standard

15	16	18	19
17	18	20	22
21	22	22	24
23	24	25	26

Ave. Int.=20.75
Grad. Magnitude=5.81
(a)

23	28	37	51
23	23	27	36
21	19	18	23
20	18	19	19

Ave. Int.=25.31
Grad. Magnitude=13.29
(b)

D	B	B	B
D	D	B	B
D	D	D	D
D	D	D	D

(c)

161	140	113	87
153	131	103	78
147	121	91	67
141	112	80	58

Ave. Int.=111.43
Grad. Magnitude=56.76
(d)

B	B	B	D
B	B	D	D
B	B	D	D
B	B	D	D

(e)

Fig. 9. (a) A uniform block. (b) and (d) Two non-uniform blocks. (c) and (e) B- and D-pixels of (b) and (d).

image database for this purpose. Also, there is no agreement on the type and the number of images in the database. However, since most image retrieval systems are intended for general databases (Albanesi et al., 2001), it is reasonable to include various semantic groups of images in the database.

Muller et al. (2001) have proposed to use image databases which are freely available. Using a common and accessible database will provide the researchers with the opportunity to compare the results of different indexing methods. We used 2250 images from two different collections: 1250 images from the database of the CSE Department, University of Washington (ANN, 2002), and 1000 images from the database of the SIMPLIcity project (Wang et al., 2001).

4.2. Distance measure

Different types of distance measures are studied and surveyed (Mehtre et al., 1995, 1997; Antani et al., 2002; Santini and Jain, 1999; Androutsos et al., 1998; Brunelli and Mich, 2001; Rubner et al., 2001). The most commonly used measures are two special cases of the Minkowski metric, L_1 and L_2. In practice, the L_1 distance performs better than L_2 (Huang et al., 1997). Using the L_1 distance, we define the distance between the query and target images by Eq. (5).

$$D(q,t) = \alpha_1\left(\alpha_3\left(\sum_{i=1}^{54}|\mathrm{HUCUB_q}(i) - \mathrm{HUCUB_t}(i)| + \sum_{i=1}^{1431}|\mathrm{HBCNB_q}(i) - \mathrm{HBCNB_t}(i)|\right)\right) + \alpha_2\left(\alpha_4\sum_{i=1}^{32}|\mathrm{HDCIG_q}(i) - \mathrm{HDCIG_t}(i)|\right) \quad (5)$$

where q and t denote query and target. α_3 and α_4 are normalization parameters that are set to 0.5 and 0.125. The maximum values of the terms that are multiplied by α_3 and α_4 are 2 and 8, respectively. α_1 and α_2 specify the effect of color and intensity features, respectively. In a complete system, these 2 parameters must be tuned, based on the relevance feedback from the user. In this work, they are both set to 0.5.

4.3. Evaluation method

There are many evaluation techniques for image retrieval, some of them inspired from the field of information retrieval (Muller et al., 2001). There is no agreement on the evaluation measures that must be used. Different researchers use different performance criteria, according to their subjectivities. However, the most common evaluation measures are different types of precision and recall.

In this paper, we use the retrieval efficiency (Mehtre et al., 1995). If the number of images retrieved is lower than the number of relevant images, retrieval efficiency represents the precision, otherwise the recall (Eq. (6)).

$$(\text{Retrieval efficiency}) = \begin{cases} \dfrac{\text{No. of relevant images retrieved}}{\text{Total no. of images retrieved}} & \text{If no. of retrieved images} \\ & < \text{no. of relevant images} \\ \dfrac{\text{No. of relevant images retrieved}}{\text{Total no. of relevant images}} & \text{Otherwise} \end{cases} \tag{6}$$

5. Results

Our query set includes 990 images of various types. Some examples are given in Fig. 10. The relevant images to each query have been found manually. Their number varies between 40 and 100.

In order to test the proposed indexing method, we compare it with a simple color histogram method, SCH, with 54 quantization levels in the HSV space. The experimental results are summarized in Table 1, where the average retrieval efficiencies, for 990 queries, are reported. The retrieval results for 3 sample queries are given in Figs. 11–13, where the most similar images retrieved, are presented.

6. Conclusion

In this paper, we introduced a novel technique for image indexing. In this technique, the image is divided into 4×4 blocks and the intensity gradient in each block is found. The histogram of gradient changes between the neighboring blocks is created to represent the shape content of the image. The image blocks, based on their intensity gradient, are categorized into uniform or non-uniform. Each uniform block is labeled by its average color. The histogram of uni-color blocks is then generated to represent the color distribution of the image. On the other hand, each non-uniform block is segmented into dark and light regions and is labeled by two average colors of these regions. The histogram of bi-color blocks is then constructed to represent the distribution of local color adjacency within the image.

Fig. 10. Ten sample query images.

Table 1
Average retrieval efficiency versus the number of images retrieved, computed over 990 queries

Method	Number of retrieved images										
	5	10	20	30	40	50	60	70	80	90	100
SCH	0.694	0.623	0.547	0.505	0.459	0.433	0.409	0.411	0.432	0.445	0.449
Proposed method	0.823	0.761	0.688	0.644	0.608	0.578	0.551	0.558	0.578	0.589	0.605

Fig. 11. Sample query 1: The image on the top left is the query. Ordered from left to right and top to bottom are the images retrieved.

Fig. 12. Sample query 2: The image on the top left is the query. Ordered from left to right and top to bottom are the images retrieved.

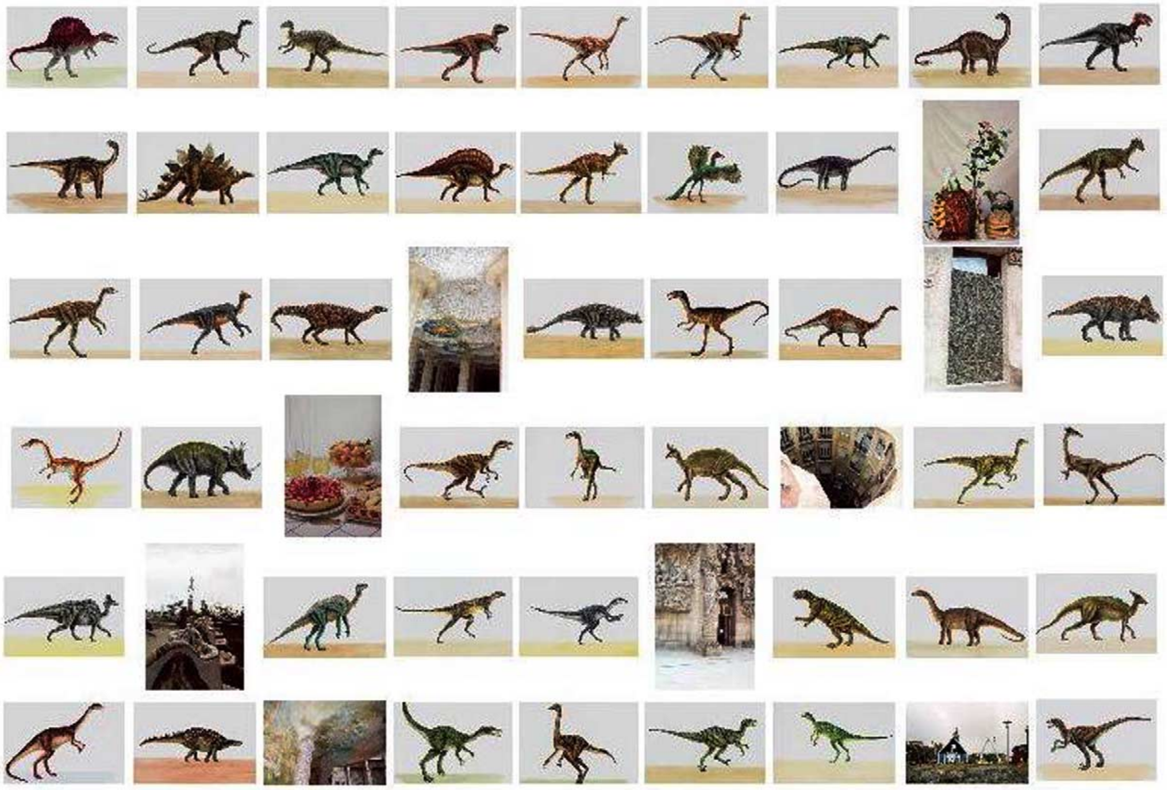

Fig. 13. Sample query 3: The image on the top left is the query. Ordered from left to right and top to bottom are the images retrieved.

The proposed indexing method was tested on a database of 2250 images and yielded very promising results. It seems that the key feature of the method is in the way that the intensity gradient and color adjacency data are exploited to build the histogram of bi-color non-uniform blocks. It is also worth noting that the color histograms represent within-block features, while the histogram of gradient changes represents between-block features in a lower resolution.

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