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Research paper

A Novel Content-based Image Retrieval System using Fusing Color and Texture Features

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Abstract

Content-based image retrieval (CBIR) systems compare a query image with images in a dataset to find similar images to a query image. In this paper, a novel and efficient CBIR system is proposed using the color and texture features. The color features are represented by color moments and color histograms of RGB and HSV color spaces, and the texture features are represented by localized Discrete Cosine Transform (DCT) and localized gray level co-occurrence matrix and local binary patterns (LBPs). The DCT coefficients and gray level co-occurrence matrix of the blocks are examined for assessing the block details. Also, LBP is used for rotation invariant texture information of the image. After feature extraction, the Shannon entropy criterion is used to reduce the inefficient features. Finally, an improved version of Canberra distance is employed to compare the similarity of feature vectors. The experimental analysis is carried out using precision and recall on the Corel-5K and Corel-10K datasets. The results demonstrate that the proposed method can efficiently improve the precision and recall, and outperforms the most existing methods.

1. Introduction

The real-world image-based applications are increasingly complex and ever more encompassing these days. Especially, more information and parameters are available to obtain the complexities of an image, which cause the amount of image data obtained and stocked in archival environments to expand rapidly. Additionally, storage, retrieval, and interpretation of a high number of images are involved in these conditions, causing further serious difficulties [1].

In the recent years, retrieval of stocked imaging data through image sets has been introduced as one of the significant focuses in the field of informatics research for use in real-world research, education, and applications [2]. In this regard, a system known as content-based image retrieval (CBIR) could be utilized for such goals. CBIR can return a collection of images from an image dataset by using the automatically elicited visual image characteristics specified as a search criterion to meet the user demand [3]. These similarity evaluation characteristics involve, but may not be restricted to, the similarities of the image content, edge pattern, color, texture, and spatial arrangement of the target area. Hence, a CBIR system provides a beneficial technique for achieving, searching, and retrieving a collection of like images in real-world applications. Different from conventional text-based approaches, CBIR does not require manual image annotation, as it is not possible today due to the massive volume of images contained in the real-world archives [1]. CBIR aims at retrieving images associated with a certain inquiry from extremely large image databases based on imparting two prominent steps. As such, at first, the images are identified via a class of features; then those images that are similar to the inquiry one are retrieved. In order to yield high-performance results, the basic step of a CBIR system is the representation of an image using discriminative, descriptive, and informative features. In this regard, several studies have been proposed to elicit the embedded data in the image via straightly calculating the features of the image from an image [4–6]. For instance, based on the discrete cosine transform (DCT) coefficients, Poursistani *et al*. have presented a modified image retrieval method in which the features are extracted from the JPEG compressed images [6]. Furthermore, the systems designed based on machine learning approaches have been greatly capable of improving the retrieval results by detecting and extracting high-level features like objects. However, the time complexity in the detection of such features is considered their most important weakness [7].

In the recent years, the fusion techniques have attracted much attention due to their high performance, and many researchers are still encouraged to employ them in the CBIR systems for different purposes. Data fusion merges the retrieval outcomes of several different systems. In other words, in the data fusion process, two or more lists of multiple data are ranked, and then these lists are merged into a ranked list to provide a better efficiency than all of the systems employed for data fusion [8]. In this spirit, various image retrieval methods based on multi-feature fusion have been proposed recently [9, 10]. It is primarily because of the simplicity of the global feature methods and the low feature dimensions. For instance, in [11], the color difference histograms (CDH) are proposed as a novel image feature representation method for image retrieval. To calculate CDH, a uniform perceptual color difference is counted between two points in accordance with the edge directions and different color backgrounds. The approach in [12] has applied color and texture features to develop an image retrieval system. The authors utilized this approach in corporation with color histograms for the color features. They also used block variation of local correlation coefficients (BVLC) and block difference of inverse probabilities (BDIP) as the texture features. In [13], features of color and texture have been fused for image representation. To construct the feature vector, their proposed fusion method uses color properties in the HSV and RGB domains along with the norm of low-frequency components of wavelet transform. In [14], the edge orientation similarities and underlying colors have been used to describe an image, which is named a micro-structure descriptor. In [15], block wise DCT has been used to elicit the texture features. Moreover, in this study, moments of colors including mean, deviation, and skewness have been utilized to elicit the color features. A new descriptor based on variations in intensity, edges, and color has been proposed for describing an image [16].

In this study, a simple but influential new scheme is introduced for the CBIR system as visual analytics in image retrieval. The proposed method used an efficient feature fusion scheme, which combines color and texture information for describing the image content. In order to derive the texture data of the image, an image is first segmented into non-overlapped blocks. After that, the wavelet transform is computed for each block. Then, the feature map is created by the inverse wavelet transform of two detailed sub-bands after eliminating the LL and HH sub-bands. This feature map represents the primitive details of the block. To extract the features, DCT of the feature map is computed. L1 norm of the first row, column, and some coefficients in the zigzag scan give good texture information about each block of the image. Also, the feature of homogeneity through the co-occurrence matrix of the block is extracted. This feature estimates the detail of the viewed image. Finally, the texture data based on the rotation-invariant of the image is extracted using LBP. To extract color data from the image, color moments and color histograms of the HSV and RGB channels are used. In this way, the final feature vector is made from the fusion of these features. The Shannon entropy criterion is utilized to eliminate the redundant and irrelevant features.

The rest of the paper is organized as follows. Section 2 gives an overview of the related works on the CBIR systems. Section 3 describes a detailed description of the proposed approach. Section 4 reports the performance results of the proposed techniques. Finally, conclusions are stated in Section 5.

2. Technical Work Preparation

A brief explanation of the existing CBIR techniques is provided in this section. The CBIR techniques commonly fall inside one of two general classes, namely those based on the elicitation of local attributes and those based on the elicitation of global ones. In general, the techniques that use local features can focus on the key points or salient patches such as [17]. However, these features usually not only have high a computational complexity but also produce high-dimensional features. In this paradigm, the local feature based on occurrence histogram is generally used, which reflects the bag-of-words method related to textual documents. The bag of representation of the morphological words in terms of texture descriptors of local morphological, and visual words bag in accordance with the scale-invariant feature transform (SIFT) are such examples [18, 19]. In addition, speeded up robust features (SURF) [20] and bag of words (BOW) model [21] are some other examples of local feature methods. In contrast, the techniques that use global features extract visual features such as shape features [22], intensity features [23], color features [24], and texture features [25]. In the literature, it has been shown that the collection of local features is a suitable approach for the global explanation of an image. This is mainly because the calculation of these features is simple and also produces low-dimensional features. In this context, color histogram is one of the simple and common global features. This feature is invariant to scale and rotation. Although color histogram is widely used in the CBIR systems, it suffers from determining the spatial information of images problem [26]. Accordingly, several methods of the color descriptors type have been proposed to address this problem, to name a few, color correlograms [27], color coherence vectors [28], and the color difference histogram [29]. Texture feature is another well-known global descriptor used in the CBIR systems. There are several algorithms in the literature reported to be very effective in texture analytics related to image data including Gabor filtering [30] and gray level co-occurrence matrices [31]. The other important global feature for describing an image is known as shape. Many researchers have developed approaches based on this descriptors including curvature scale space (CSS) [32], Zernike moments (ZMs) [33], and angular radial transform (ART) [34].

3. Proposed Method

A novel and efficient CBIR method based on low-level visual attributes is introduced in this study for describing images. It is difficult to describe the content of the image based on a single feature efficiently. In order to address this problem, a simple but potent new fusion descriptor is proposed in this paper. To this end, the color and texture data are combined to get better results for the image descriptor. Figure 1 illustrates the flow chart of the proposed method. In the following, the implementation of the proposed method is explained in detail.

3.1. Color feature

Color is known as an important case of low-level visual attributes. This feature is constant. In addition, it is rarely affected by image characteristics such as translation, rotation, and scale [35, 36]. The color spaces used in this study include RGB and HSV. The components of RGB color space include green (G), red (R), and blue (B), while saturation (S), hue (H), and value (V) form the components of HSV color space. The HSV color space can be configured based on a cylinder. Also, the high simulation ability of this color space from human color perception is remarkable [37-39]. Although the human visual system cannot understand a large number of colors simultaneously, it is well capable of distinguishing similar colors from each other [40]. In the proposed method, components of R, G, B, V, S, and H are quantized into 10 values uniformly. Then, the color histogram is calculated for every component. Therefore, $10 \times 6 = 60$ color features are obtained.

Another color based feature used in this work is the color moments. It is required to segment the input image into sixteen non-overlapped blocks for the extraction of color moments to be performed. The first and second moments, i.e. mean and variance of components H, V, and S, in HSV color space are used as the color moment features. Hence, we have $16 * 2 * 3 = 96$ color moments feature.

To extract color information of images, we used color histogram and color moments. For the global color descriptor of the images, a color histogram is used. Moreover, for the local color image descriptor, the color moments are utilized.

3.2. Texture feature

In order to extract the texture feature, the input image is first segmented into sixteen non-overlapped blocks. Then by extracting some texture features from each block, the content of the block is described. In addition, the extraction of LBP is performed from the image. In what follows, the proposed texture descriptor is explained in detail.

3.2.1. Discrete wavelet transform (DWT) and discrete cosine transform (DCT)

DWT [41] is utilized in this work for extracting the texture features from the image. A given image utilizes low-pass and high-pass filters in two dimensions to decompose the image to detail (high-frequency components) and approximation (low-frequency components) coefficients. Therefore, based on the wavelet-packet decomposition manner, four sub-bands including HH, HL, LH, and LL are the result of the first decomposition level. The LL sub-band represents the approximation coefficient of the image. Moreover, the sub-bands of HH, HL, and LH indicate the diagonal, vertical, and horizontal details coefficients of an image, respectively. As mentioned earlier, the input image is first segmented into sixteen non-overlapped blocks. Then, DWT is applied on every block. In this method, one-level decomposition with the Daubechies mother wavelet is used. After that, the two sub-bands of LL and HH are eliminated. Next, the inverse discrete wavelet transform (IDWT) is fed into two detailed sub-bands (HL and LH). Figure 2 represents the proposed texture feature map for an image.

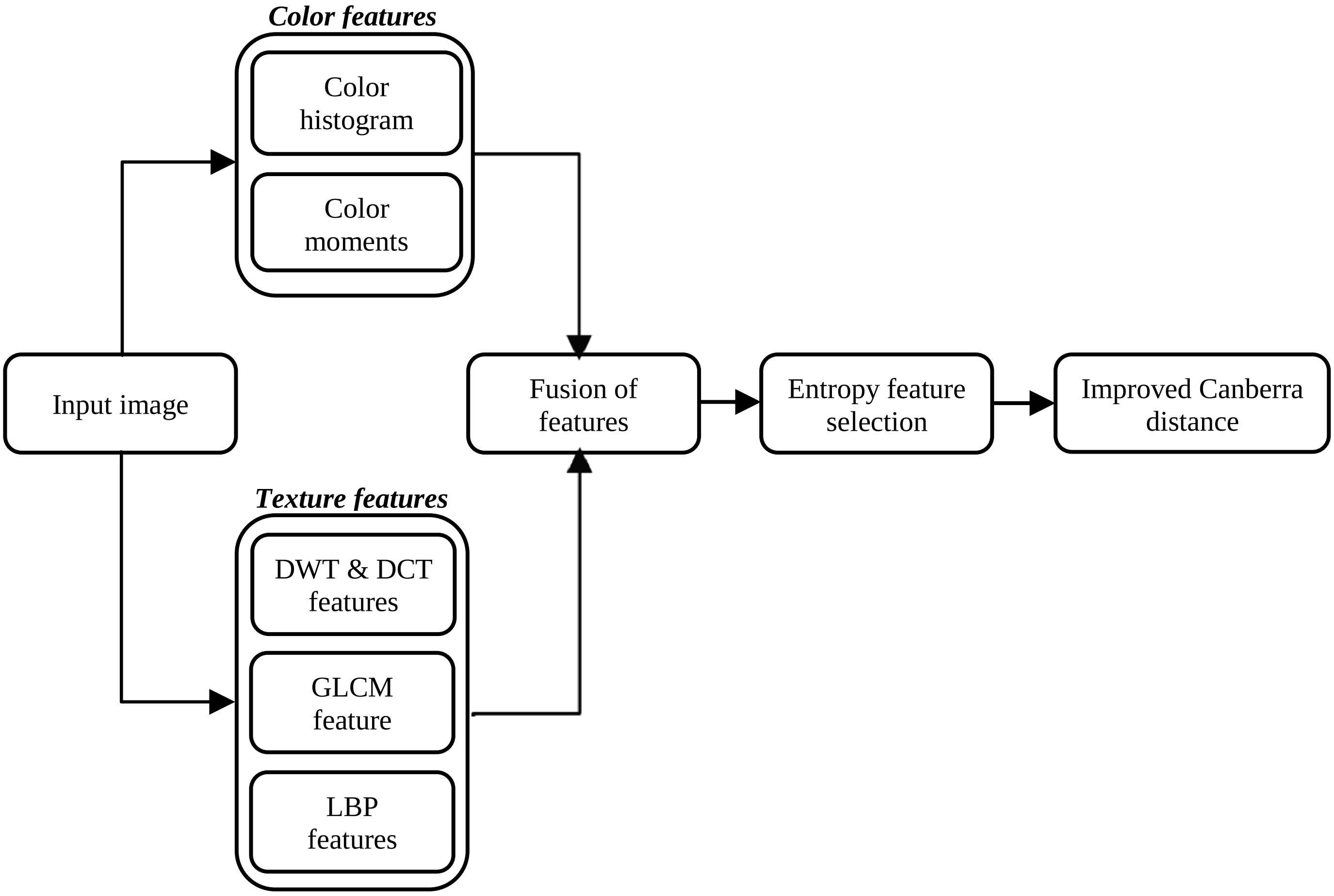
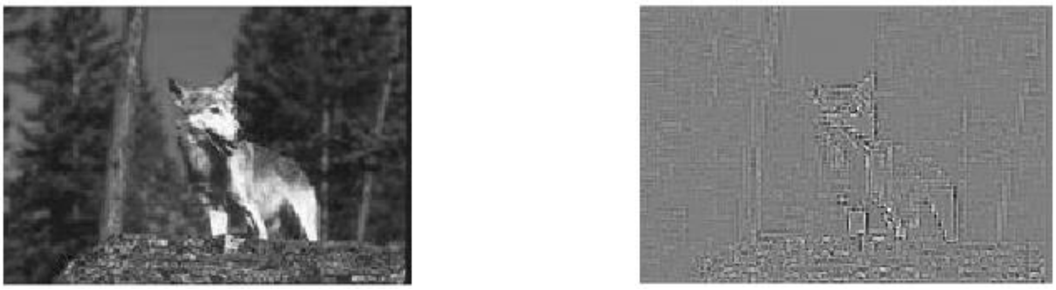


Figure 1. Flow chart of proposed image retrieval method.

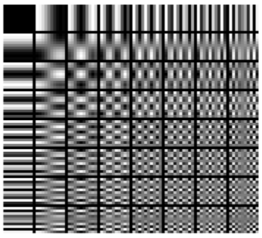


a) original image **b) texture feature map**

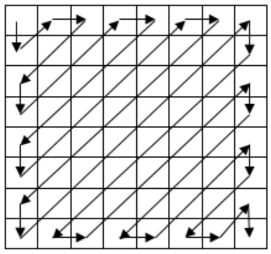
Figure 2. Representative of an image and its texture feature map based on the wavelet transform.

In order to extract the texture feature, DCT is applied on the obtained texture feature map. The vertical edge, horizontal edge, and texture information of a block of an image are available in the DCT coefficients of the block. However, for better describing the texture information of the image, first by applying DWT on the image, low-frequency information and unnecessary high-frequency information are eliminated.

Figure 3 depicts 8 × 8 DCT basis functions and DCT zigzag scan for an image. As shown in Figure 2, the element in the top-left corner denotes the DC coefficient, while each other conversion coefficients denote the AC coefficients. The AC elements in the top row and in the left column represent vertical and horizontal variations, respectively. In addition, coefficients of zigzag scan represent the order of significance of these coefficients in the human visual system behavior. Hence, the L1-norm of AC coefficients is calculated in the top row and in the left column as well as some important DCT zigzag scan coefficients. In this way, the content of each block is described using the three values obtained for it. We have 16 * 3 = 48 DCT features.



a) 8 × 8 DCT basis functions



b) DCT zigzag scan

Figure 3. Two dimensional DCT frequencies and exhibition of DCT zigzag scan.

3.2.2. Gray level co-occurrence matrix (GLCM)

GLCM is one of the important texture-based feature extraction methods. In contrast to histogram, GLCM indicates the relationship between the values of the neighbors in an image. GLCM is an N-dimensional square matrix, in which N indicates the number of gray levels in an image.

In this paper, the GLCM is a 256 × 256 matrix, where the $[i.j]^{th}$ element of this matrix represents the probability of a pixel with gray level value of i to be neighbor with a pixel with the gray level value of j. GLCM is calculated using the function $P(i,j,d,\theta)$, as follows:

$$P(i,j,d,\theta) = \#\{(x_1,y_1)(x_2,y_2) \mid f(x_1,y_1) = i, f(x_2,y_2) = j, |(x_1,y_1)-(x_2,y_2)| = d, \angle((x_1,y_1),(x_2,y_2) = \theta)\} \quad (1)$$

where i indicates the gray level value of the pixel located in (x, y) coordinates, and j is the value of the pixel located at the distance d and the direction Ө from (x, y) coordinates. GLCM is calculated for four values of Ө (0, 45, 90, and 135 degrees), and the texture features are calculated by averaging over the four GLCMs. After GLCM calculation, the homogeneity feature is estimated by the GLCM values, as follows:

$$Hom = \sum_{i=1}^{256}\sum_{i=1}^{256}\frac{P(i,j)}{1+|i-j|} \quad (2)$$

In our work, each image is divided to 16 blocks, and homogeneity feature is extracted from each block of the image. Hence, 16 features are extracted in this step.

3.2.3. Local binary pattern (LBP)

LBP is a well-known method for extracting the texture features of the image. Computational simplicity and non-parametric are considered two prominent advantages of LBP [7]. LBP is a descriptor of the local grayscale texture computed by comparing the value of a pixel with the values of its neighbors. LBP is defined as follows:

$$LBP_{N,R} = \sum_{n=0}^{N-1} s(n)(I_n - I_c)2^n$$
$$s(n) = \begin{cases} 1 & if \quad I_n - I_c \geq 0 \\ 0 & if \quad I_n - I_c < 0 \end{cases} \quad (3)$$

where I_c indicates the gray level value of the pixel located in center, I_n indicates the gray level value of its neighbor n, N indicates the neighbor number, and R indicates the radius of the neighborhood. These steps are done for every pixel of the image, and the LBP matrix is performed using the LBP values of all pixels. In some studies, the histogram of the LBP matrix was utilized as the input features [41-43]. The LBP estimation for R = 1 and N = 8 is presented in Figure 4.

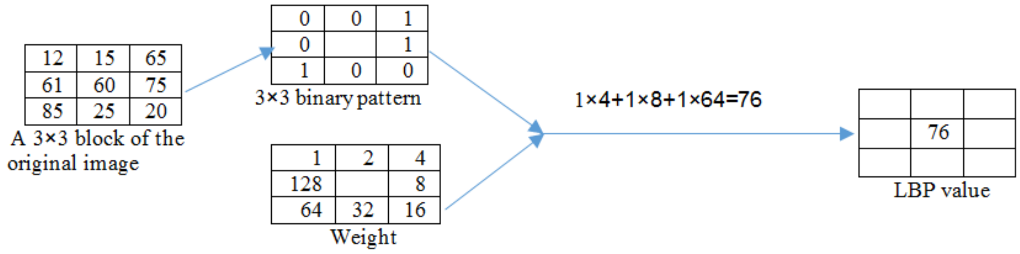


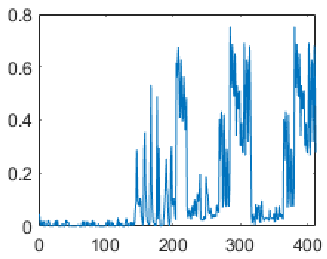
Figure 4. Representative of LBP calculation for R = 1 and N = 8.

3.3. Feature selection

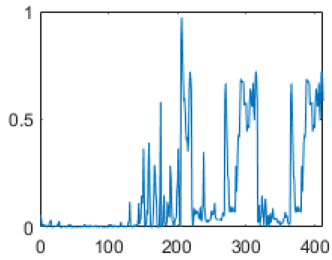
Feature selection reduces the number of calculated features to decrease the computational complexity of modeling, and, also in some cases, to improve the model performance. In this paper, the Shannon entropy criterion is used to select the superior features. The Shannon entropy represents the importance of information contained in the feature. The low value of the entropy for a feature represents that the feature is not informative enough, whereas its high value indicates the importance of the feature. Our proposed feature vector includes 459 features. After feature selection with Shannon entropy, 410 features are remained. Figure 5 shows two pictures and their proposed final features.

a) An example of image in Corel-5k dataset

b) An example of image in Corel-5k dataset



c) Proposed feature of a)



d) Proposed feature of b)

Figure 5. Two examples of proposed feature vector. Horizontal axes indicates index values for efficient features, and vertical axes indicates feature values.

4. Experimental results

In this work, we present a technique for content-based image retrieval. Our results are compared with some other new papers worked on the Corel-5K and Corel-10k datasets. We selected 20% of data from each class randomly as query images, and this process was repeated three times. Then the results of these three repetitions were averaged and used for performance evaluation.

4.1. Datasets

The Corel-5k and Corel-10k databases consist of 5000 and 10000 color images in the JPEG format, respectively. Corel-5k contains 50 classes and Corel-10k contains 100 classes. Also every class consists of 100 images in (192 x 128) and (128 x 192) size. Corel-5k is part of the Corel-10k dataset. The sample of image categories is shown in Figure 6.

4.2. Distance metric

The distance metric is a way of measuring how much data samples are distinct or closed to each other. In this work, an improved Canberra distance is used as the distance metric. Let R and K be the m-dimensional feature vectors of template and query images, respectively. An improved Canberra distance is defined as follows:

$$D(R,K) = \sum_{i=1}^{m} \frac{|R_i - K_i|}{|R_i + K_i + w \times u_k|} \tag{4}$$

in which D(R, K) is the distance value between vectors R and K, and w is a constant value, which is considered 0.01, and also $u_k = \sum_{i=1}^{m} \frac{k_i}{m}$.

Figure 6. Sample of Corel-10k database.

4.3. Performance measures

In this work, two known metrics, precision and recall metrics were utilized for evaluation the performance of the proposed algorithm. In our work, 12 images were retrieved at each step. These two metrics are defined as follows:

$$\Pr ecision = \frac{K}{N} \tag{5}$$

$$\operatorname{Re} call = \frac{K}{M} \tag{6}$$

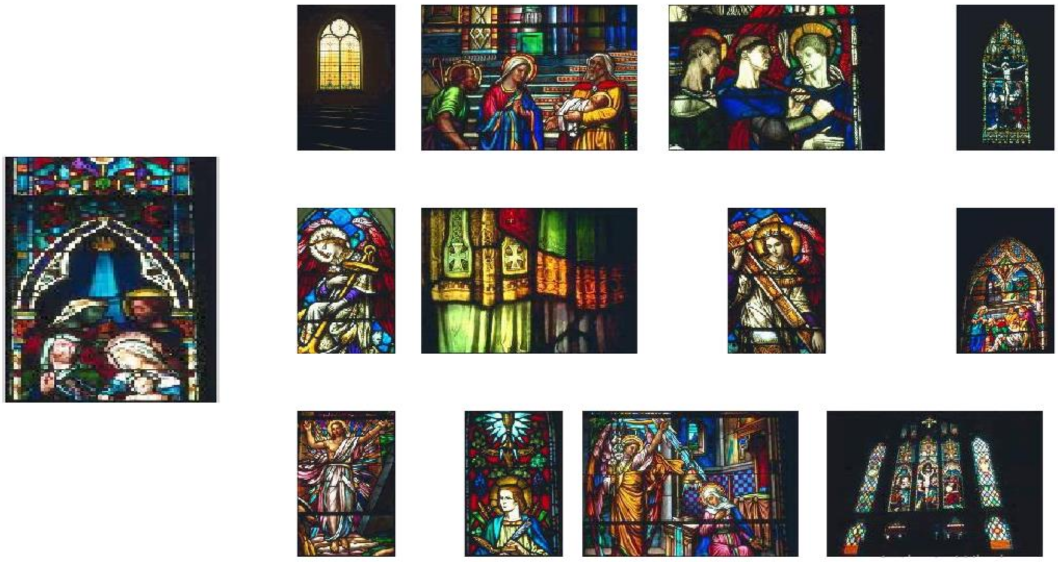
where K indicates the number of images correctly retrieved that are in the same class with the query image. N is the total number of images retrieved at each step, and M is the total number of images that are in the same class with the query image. For the two mentioned databases, M is 100 and N is 12. Higher precision and recall values show the better image retrieval performance.

4.4. Proposed algorithm evaluation

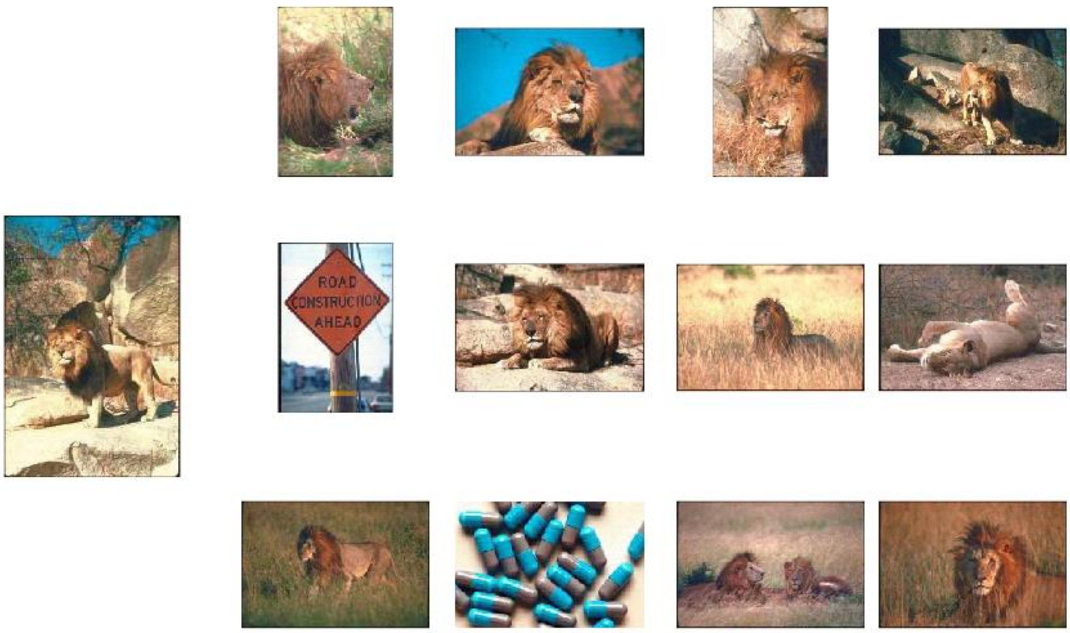
In this section, a comparison is made between our work and some other new works. As mentioned earlier, for a subjective comparison, precision and recall are used. Also 20% of the images from each class were selected as query images. Table 1 presents a comparison between results of the proposed work with some existing methods worked on Corel-5k and Corel-10k. The results indicate that our work has a better performance in term of higher precision and recall value than the other methods. Figure 7 shows two images from Corel-10k database retrieved by the proposed method. In this figure, the query image with 12 retrieved images are shown. In the first example, all of the 12 retrieved images belong to the query class. However, in the second example, two retrieved images do not match with the query image. In the proposed method, the color and texture information of the image is used to describe the content of the image. It seems that by adding the shape descriptor of the image, our proposed method will be improved. It would be our future work.

Table 1. Comparisons of proposed work with some new methods in terms of precision and recall metrics on the Corel-5K and Corel-10K datasets.

Dataset		CDH [11]	BBC [12]	LMDcP [25]	CDHT [29]	HCSF [24]	[7]	Proposed method
Corel-5K	Precision (%)	57.23	57.5	47.12	59.51	61.82	62.64	64.14
	Recall (%)	6.87	6.90	5.74	7.21	7.41	7.58	7.70
Corel-10k	Precision (%)	45.24	47.01	–	49.31	50.67	51.06	53.18
	Recall (%)	5.43	5.64	–	5.88	6.08	6.28	6.38



a) Left image is query image, and all returned images are correctly retrieved and ranked within top 12 images.



b) Left image is query image, and 10 images are correctly retrieved and ranked within top 12 images.

Figure 7. Two image retrieval examples made by proposed algorithm on Corel-10k dataset.

5. Conclusion

This work presented a new image retrieval system that used a fusion of low-level features. The proposed feature vector not only describes color information by combining the HSV and RGB color spaces but also extracts texture features by combing information on edges and intensity variations. Finally, the experiments on two different databases confirmed that the proposed algorithm in terms of accuracy of image retrieval was efficient compared to some existing methods.

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