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Content-Based Image Retrieval Using HSV Color Space Features

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***Abstract*—**In this paper, a method is provided for content-based image retrieval. Content-based image retrieval system searches query an image based on its visual content in an image database to retrieve similar images. In this paper, with the aim of simulating the human visual system sensitivity to image's edges and color features, the concept of color difference histogram (CDH) is used. CDH includes the perceptually color difference between two neighboring pixels with regard to colors and edge orientations. Since the HSV color space is close to the human visual system, the CDH is calculated in this color space. In addition, to improve the color features, the color histogram in HSV color space is also used as a feature. Among the extracted features, efficient features are selected using entropy and correlation criteria. The final features extract the content of images most efficiently. The proposed method has been evaluated on three standard databases Corel 5k, Corel 10k and UKBench. Experimental results show that the accuracy of the proposed image retrieval method is significantly improved compared to the recently developed methods.

***Keywords*—**Content-based image retrieval, color difference histogram, efficient features selection, entropy, correlation.

I. Introduction

IMAGE retrieval is one of the well-known and currently hot research subjects in the field of computer vision. Content based image retrieval (CBIR) systems search the queried digital image in a large dataset using the image contents rather than the metadata such as keywords and tags. To have an effective CBIR, using only low-level features like color, texture, and the shape of objects is not enough. Low-level features could describe the simple content of images, but not the high-level concepts [1], i.e. the objects and relation between them in an image. This issue is one of the most important challenges in the CBIR system which is known as Semantic Gap.

Different CBIR systems might provide different results (see Fig. 1). There are two major categories of solution to solve the semantic gap issue. The first category focuses on using high-level features including object recognition, machine learning and deep learning. The second category uses a combination of low-level features. Methods in the first category need a lot of images for training purpose, which is more time consuming, while methods in the second category do not need such amounts of data. In this paper, we use a combination of low-level features to extract the semantic of images, which results in a CBIR system with a reasonable retrieval rate and higher mean average precision in comparison to other CBIR methods.

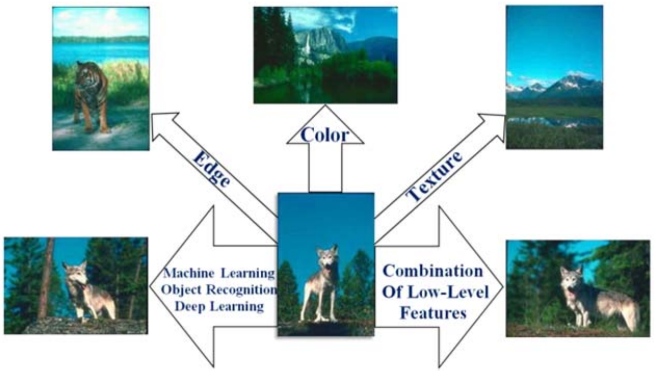

Fig. 1 Various CBIRs may provide different image depending to the employed technique

Some high-level feature based CBIRs have used machine learning methods to classify different images [2], [3], the Bayesian framework for ranking image class [4], and the convolutional network for image segmentation [5], [6]. There are also some deep learning based methods for object recognition [7] and image classification using neural network [8], [9]. A comprehensive review on CBIR systems has been provided in [10].

Another method for image retrieval has been proposed in [11], which uses relevance feedback in combination with low-level features. Relevance feedback is a multi-steps method which is an interface between the user and the image retrieval system. This method uses the user's feedback and machine learning methods to increase the accuracy of system iteratively.

In the literature, a number of image retrieval methods have been proposed which are based on the second solution category, like combination of color and texture features [12], and combination of color, texture and shape features [13], [14]. Also, in another paper, the color image is first converted to color strings comparison, then these strings is used as feature vectors for retrieving the images [15].

In [16], to extract the texture feature set, the authors used a histogram called a micro structure. The micro structure is extracted from the HSV color space of images. In this method, a 3-by-3 filter moves on the images to find some edges which

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have the same direction, which are considered as micro structures. Then the histograms of pixels, which are close to these structures, have been used for image retrieval [16].

In [17] to simulate the human visual system, the authors used a descriptor called MTH (Multi Texton Histogram). MTH uses the first- and second-order statistics to analyze the texton, and therefore, the texture extraction is more accurate. MTH can present the spatial correlation of colors and edges using textons analysis. The MTH uses the spatial correlation of pixels in the same neighborhood based on four special texton types.

Singh et al. [18] proposed a fast and efficient image retrieval system based on color and texture features. The texture features are extracted from block difference of inverse probabilities (BDIP), block variation of local correlation coefficients (BVLC) and color features. It is observed that the color features in combination with the texture features derived from the brightness component provides approximately similar results when the color features are combined with the texture features using all three components of color, but with much less processing time [18]. This method is one of the newest, fastest and most accurate CBIR methods.

Psychophysical and neurobiological researches show that the human visual system is very sensitive to color and edge orientation [19]-[21]. The authors in [19] presented a novel image retrieval method using psychophysical and neurobiological features, namely CDH which resulted in a highly accurate CBIR system. Based on the pixel color and edge orientation, CDH method counts the uniform color difference between two locations with different backgrounds in L*a*b* color space, which makes this method unique. This method is considered as a novel visual attribute descriptor by considering color and edge orientation, without using either machine learning methods nor clustering and segmentation methods.

Inspired from [19], in this paper a CBIR method based on psychophysical and neurobiological characteristics to simulate human visual systems is proposed. It has been shown in the paper that human visual characteristics could be presented effectively and more accurately in the HSV color space than the L*a*b* color space. Therefore, instead of using L*a*b* color space, the CDHs features are extracted in the HSV color space. In addition to the CDH features, to increase the accuracy of the proposed method, some features from the color histogram in HSV space will be extracted too. Then, to increase the accuracy and the retrieval rate of this system, Shannon entropy and feature correlation methods will be used to select the effective features. Experimental results show that the accuracy of the proposed method is significantly higher than MTH [17], MSD [16], CDH [19] and BBC [18].

The rest of this paper is organized as follows. The proposed CBIR system will be explained in Section II. In Section III, experiments will be presented and analyzed. The paper concludes in Section IV with a discussion of the results achieved and some suggestions for future work.

II. Proposed Method

The proposed CBIR method has three major steps: Feature extraction, feature selection and similarity measurement.

In the first step, a number of features are extracted from the color histogram and CDH in the HSV space from the query image ($\boldsymbol{\varphi}$) and the dataset images ($\boldsymbol{Q}^L$). In the second step, by computing the entropy of each feature among all the images, ineffective features (δ_i) will be excluded. Then by calculating the correlation between the remaining features, redundant features will be removed. This process will improve the retrieval rate of the proposed method significantly. After selecting the effective features, the corresponding feature set values for the query image and each image in the dataset are calculated. Finally, the similarity (R^L) between the query image feature set ($\boldsymbol{\Phi}'$) and dataset feature sets ($\boldsymbol{Q}'^L$) is calculated using improved Canberra. Fig. 2 shows the diagram of the proposed method.

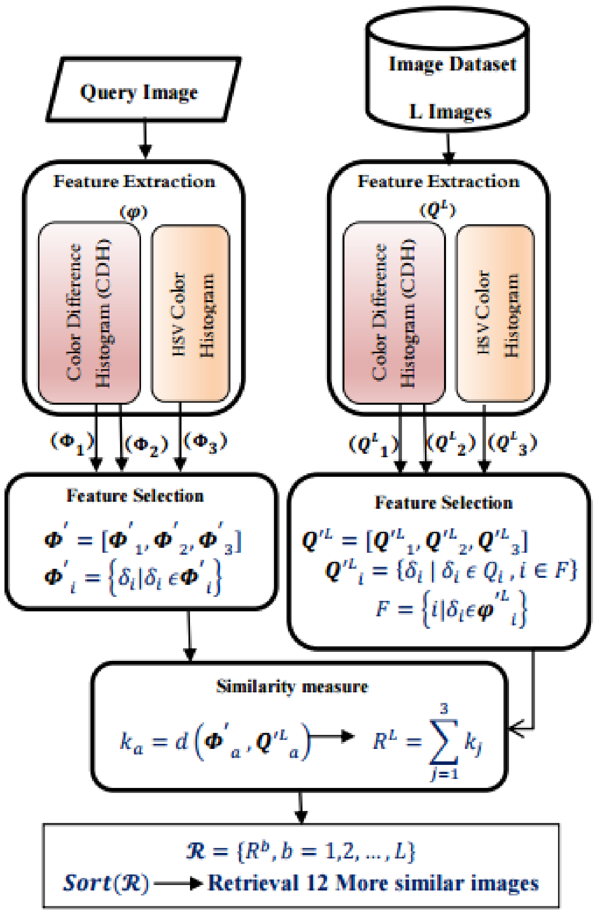


Fig. 2 Diagram of proposed method for image retrieval

A. Feature Extraction

As mentioned earlier, in this paper a combination of low-level features will be used for retrieving images which makes the calculation load very light. These low-level features are extracted from the color histogram and color differential histogram of an image in the HSV color space. In this section the proposed features are explained:

1) CDH

As mentioned before, psychophysical and neurobiological researches show that the human visual system is highly sensitive to image color and edge orientation. Therefore, the perceptual color difference between pixel colors and edge orientations contains much information about the image [19]. In our method, the pixel color difference is calculated in such a color space that has a perceptually uniform color difference. In a perceptual uniform color space, the difference between two colors is proportional to the Euclidian distance within the given color space [22].

Among all color spaces, L*a*b* and HSV have the mentioned perceptual characteristic. In [19], to extract the features from the CDH, the L*a*b* color space has been used. However, since the HSV color space has the same characteristic (perceptual uniform color difference), this color space is used for extracting the features from the CDH. In our method, each H, S and V channel is quantized to 8 level, 4 level and 4 level, respectively. Experimental results show that the extracted features from this color space are able to present the content of images better than the L*a*b* color space, while the retrieval rate has been increased significantly too.

Edge orientation has a significant effect on human visual perception. Edges could be a good representative of objects and texture structures, providing the most important information about the image content [19], [23]-[25]. In our method, after quantization of the images in the HSV color space, the edge orientation will be calculated using Sobel operator which is a powerful edge operator for detecting the color difference in a perceptual color space. Then, the calculated orientation values will be quantized to m values. Guang-Hai et al. [19] experimentally showed that the best value for m in HSV color space is 36.

Now, let us explain how CDH values are calculated. Consider the values of a quantized color image $A(x,y)$ are shown as $a \in 0,1,\dots,A-1$. Also, neighboring pixels locations are shown by (x,y) and (x',y') and their color index values as $A(x,y)=a_1$ and $A(x',y')=a_2$. The values of an edge orientation $\theta(x,y)$ are shown as $b \in 0,1,\dots,B-1$. The angles at pixels (x,y) and (x',y') are denoted by $\theta(x,y)=b_1$ and $\theta(x',y')=b_2$. For the neighboring pixels, whose distance is 1 and quantization numbers for the color and edge orientations are A and B, respectively, the CDH is defined as follows:

$$H_{color}(A(x,y)) = \begin{cases} \sum\sum\sqrt{(\Delta H)^2+(\Delta S)^2+(\Delta V)^2} \\ where\ \theta(x,y)=\theta(x',y'); \\ (|x-x'|,|y-y'|)=1 \end{cases} \quad (1)$$

$$H_{ori}(\theta(x,y) = \begin{cases} \sum\sum\sqrt{(\Delta H)^2+(\Delta S)^2+(\Delta V)^2} \\ where\ A(x,y)=A(x',y'); \\ (|x-x'|,|y-y'|)=1 \end{cases} \quad (2)$$

where ΔH, ΔS and ΔV are the color differences between two neighboring pixels in the H, S and V channels, respectively. $H_{color}(A(x,y))$, a 128-dimensional vector, represents the perceptual color difference between neighboring edge orientations by considering the color information. $H_{ori}(\theta(x,y))$ shows the perceptual color difference between neighboring color indexes using edge orientation, which leads to a 36-dimensional vector; in total, a $128+36=164$-dimensional vector is extracted for the first image features during our image retrieval system. Then $H_{color}(A(x,y))$ and $H_{ori}(\theta(x,y))$ are combined as the first part of the image feature set:

$$H_{CDH} = \begin{bmatrix} H_{color}(0), H_{color}(1),\dots,H_{color}(A-1), \\ H_{ori}(0), H_{ori}(1),\dots,H_{ori}(B-1) \end{bmatrix} \quad (3)$$

The experimental results shown in [19] demonstrated that $A=128$ and $B=36$ are most suitable for these features.

2) Color Histogram

As mentioned before, the color space which is used for feature extraction plays a very important role in CBIR systems. Such a color space should be close to human visual system. As mentioned in the previous section, among all color spaces, HSV and L*a*b* color spaces have the perceptually uniform characteristic. The HSV color space is widely used in image retrieval and object recognition systems [26]-[28].

It is shown in this paper that the features extracted from the histogram in HSV color space describe the image content better than the same features extracted in L*a*b* color space. Therefore, in this paper HSV color space has been used to extract some features from the color histogram. HSV color space has three components, including Hue (H), Saturation (S), and Value (V). HSV is a cylindrical geometry with hue, their angular dimensions, starting at the red primary at 0°, passing through the green primary at 120° and the blue primary at 240°, and then wrapping back to red at 360° [29].

Since the hue component is more important than the two other components, this component is quantized to 18 values, while the saturation and value component are quantized to three values. The combination of all these values results in 162 different colors which creates the second part of the image feature set.

B. Feature Selection

As mentioned before, there are 128 features of the color differential histogram (related to color), 36 features of the color differential histogram (related to edges) and 162 features of the color histogram in HSV color space. In this paper, two methods including entropy and feature correlation are used to select the effective features. Next, each method is explained briefly.

In this paper, entropy (more specifically, Shannon entropy) is the expected value of the information contained in each feature among all images. The following equation is used for computing the entropy of feature x:

$$En(X) = -\sum_{i=1}^{n} P(x_i)\log_2 P(x_i), \quad (4)$$

in which $P(x_i)$ is the probability of value x_i in feature x. The entropy of features for both color differential histogram and color histogram in HSV color space will be calculated separately. Using entropy, the features that have less/no information will be excluded which results in an image retrieval system with higher performance.

In the next step, the redundant features will be removed, resulting in an increase in the retrieval rate of our method. To do this, the correlation of each pair of features is calculated. The correlation rate is a number between [-1, 1] which shows a positive or negative correlation between two features. If there is no correlation between two features, the correlation rate will be zero. To calculate the correlation rate between two features X and Y with n values, the following formula is used:

$$Corr(X,Y) = \frac{n\sum x_i y_i - \sum x_i \sum y_i}{\sqrt{n\sum x_i^2 - (\sum x_i)^2}\sqrt{n\sum y_i^2 - (\sum y_i)^2} \quad (5)$$

Once there is a correlation between two features, they have the same information, and removing one of them will not affect the accuracy of the proposed method. Experimental results show that 10 features of the CDH and 31 features of the color histogram are redundant and removing these features increases the accuracy of our method slightly. Finally, 61 features of the CDH and 23 features of the color histogram in the HSV color space will be used as the final feature set, containing 84 features in total. Fig. 3 shows the final features for two images.

III. Experiments

The performance of the proposed algorithm is evaluated using three Corel-5k, Corel-10k and UKBench datasets in this section. For fair comparison, algorithms that were originally developed for image retrieval are selected; they include the micro-structure descriptor (MSD) [16], MTH [17], BBC [18] and CDH [19]. In the following, the datasets are described briefly and then performance of the proposed method will be represented.

A. Datasets

There are lots of datasets for evaluating CBIR methods such as Corel5K, Corel10K, UKBench, Caltech101 and PASCAL VOC. Corel dataset has been used more than others for evaluating the image retrieval systems. This dataset includes images with various contents including those of different animals, sports and nature; we used two subsets of this dataset to evaluate the proposed method. The first subset is Corel5K which has 5,000 images in 50 different classes. Each class includes 100 images. The size of images is 128*192 or 192*128 in .jpg format. The second dataset includes 10,000 images, in 100 different classes, called Corel10K. Like Corel5K, each image size is 128*192 or 192*128, in .jpg format [30]. The last dataset that will be used in this section is UKBench with 10,200 images, this database includes 2,550 classes and each class has 4 images with size of 480*640 each [31].

B. Performance Metrics

To evaluate performance of the proposed methods, we use the Precision and Recall as defined below:

$$P = {}^{I_N}/_{N} \quad (6)$$

$$R = {}^{I_N}/_{M} \quad (7)$$

where I_N is the number of images retrieved correctly, M is the total number of images that are similar to the query image, and N is the total number of images retrieved. In this image retrieval system, for Corel databases, N = 12 and M = 100 and for UKBench database, N = 4 and M = 4. A higher precision and recall indicates a better retrieval performance.

In some experiments, to calculate the more accurate image retrieval rate, mean average precision (MAP) and mean average recall (MAR) are used. These criteria are as follows:

$$\text{MAP} = \frac{\sum_{i=1}^{Y} P_i}{Y} \quad (8)$$

$$\text{MAR} = \frac{\sum_{i=1}^{Y} R_i}{Y} \quad (9)$$

where, Y is the number of all images in database (in this paper, these criteria will be applied to the Corel-5K database and are 5,000). P_i and R_i are the precision and recall of image retrieval, respectively.

C. Distance Metric

The performance of retrieval not only depends on a strong feature set, but also on efficient distance metrics. There are a lot of distance metrics for image retrieval [32]-[34]. The study experimented on different criteria; finally, the improved Canberra [19] was used for image retrieval system defined as:

$$D(T,Q) = \sum_{i=1}^{M} \frac{|T_i - Q_i|}{|T_i + u_T| + |Q_i + u_Q|} \quad (10)$$

where D is the distance metrics, T and Q are feature vectors respectively, M, u_T and u_Q are the length of the feature vector, the mean of the feature vector T and Q, respectively.

TABLE I
The Mean Average Retrieval Precision and Recall of CDH and Color Histogram with Different Color Spaces

Features	Performance	Color Spaces	
		L*a*b*	HSV
CDH	MAP (%)	55.89	56.57
	MAR (%)	6.70	6.78
	N	108	164
Histogram	MAP (%)	37.80	40.56
	MAR (%)	4.53	4.86
	N	90	162

A. Color Space

As mentioned before, the pixel color difference is calculated in such a color space that has a perceptually uniform color difference characteristic. Recently researches showed that among all color spaces, L*a*b* and HSV have the mentioned characteristic. In this experiment, the CDH and color histogram in these color spaces are extracted and compared. To compare, we use the length of feature vector, MAP, and MAR criteria on all of images in the Corel-5k database. The results of this experiment are shown in Table I.

As shown in Table I, the extracted features in the HSV color space result in a higher precision. Although the feature vector length in HSV color space is higher than L*a*b* color space, the next experiment shows that the length of feature vector can be reduced from 164 and 162 to 61 and 23, respectively, by maintaining the accuracy not only at the same level, but also by improving it slightly. This result shows that the HSV color space is able to simulate the human visual system and describes the content of images better than the L*a*b* color space.

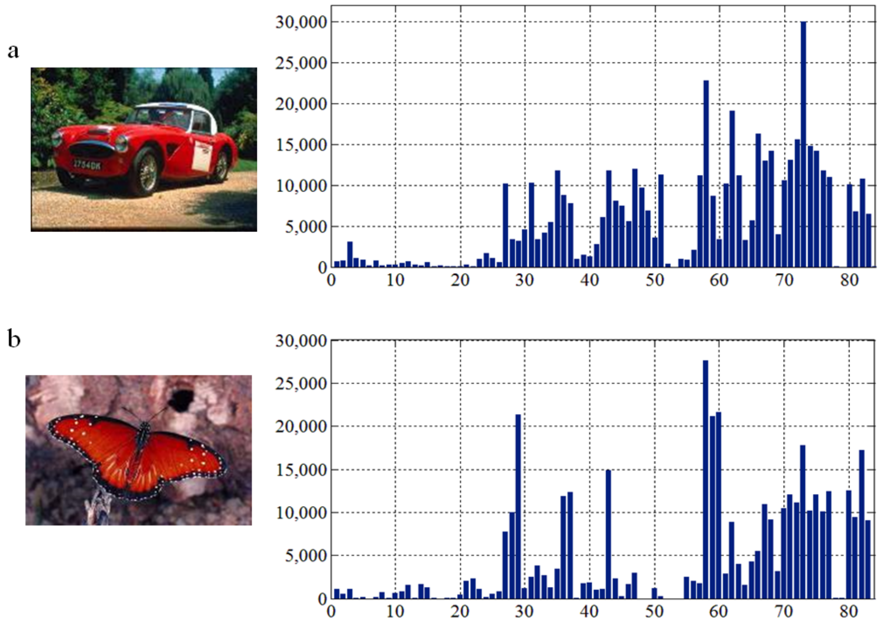


Fig. 3 Two examples of using the proposed method: (a) Car and (b) The butterfly; the horizontal axes corresponds to the index values for efficient features (where values in the range 1–23 denote color histogram and values in the range 24–68 denote color of CDH and values in the range 69–84 denote edge orientation of CDH). The vertical axes corresponds to color and perceptually color difference values

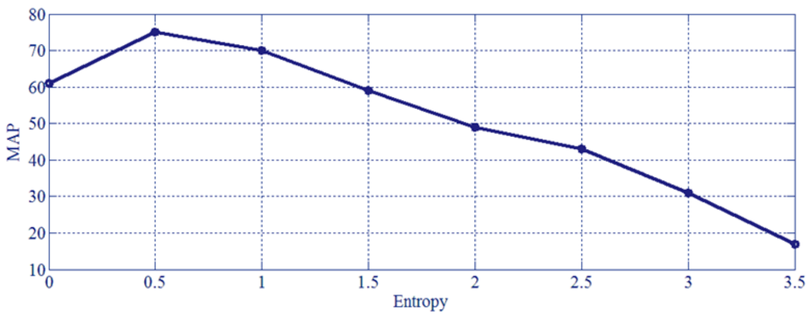


Fig. 4 The mean average retrieval precision of CDH By removing features based on entropy

B. Efficient Selection Features

After selecting the appropriate color space and extracting the feature set, the next step of the proposed method is to reduce the number of features. In this step, using entropy and feature correlation, some redundant and inefficient features will be removed.

A randomly subset of 1,000 images of Corel5k has been selected as the validation data for the purpose of feature selection. The validation data include 50 classes, each of which contains 20 images.

First, the entropy of each feature extracted from the CDH is calculated. Then to select the efficient features, the MAP on the validation images is computed. In each iteration, the features with entropy lower than threshold x are excluded and then the MAP is calculated again. In this paper, $x = 0, 0.5, 1, \ldots, 3.5$.

Fig. 4 shows how the MAP is changed for different values of x. Based on this experiment, x=0.5 results in the highest MAP on validation data. At x=0.5, among all 164 features, the entropy of 91 features is less than 0.5, which results in 71 remaining features: 46 features of the remaining features are derived from color and 25 features are derived from edge orientation.

The entropy calculation is applied on 162 features derived from the color histogram in the HSV color space too; however, based on the experimental results, the highest MAP is gained when the features with entropy less than 1.5 are excluded. Hence, among 162 features, 108 features are removed, which results to have 54 remaining features with entropy higher than 1.5.

In the next step, the feature correlation method has been used to remove the redundant features. The same validation dataset has been used for this experiment. For 71 remained features, which are extracted from the CDH, the correlation of each feature with others is computed. If the correlation between the two features is higher than threshold y, then one of these two features should be removed; hence, as the second part of the decision (removing one of two mentioned features), a feature that has a lower correlation to the desired output vector will be removed. The desired output vector is created by indexes of validation images classes.

Experimentally, it was found that by considering the threshold y = 0.9, not only the number of remaining features (extracted from CDH) could be reduced from 71 to 61, but also the accuracy of the method could be improved slightly.

By applying the same process and the same threshold y = 0.9 on the 54 remaining features of the color histogram, 31 redundant features were removed, and 23 final features of the color histogram could be used for image retrieval.

Table II shows the MAP on the validation dataset for each step of feature reduction process. As shown in this table, by reducing the number of features, the MAP is improved slightly. In this experiment, it was found also that removing features that have negative correlation with the desired outputs could improve the accuracy of the proposed method.

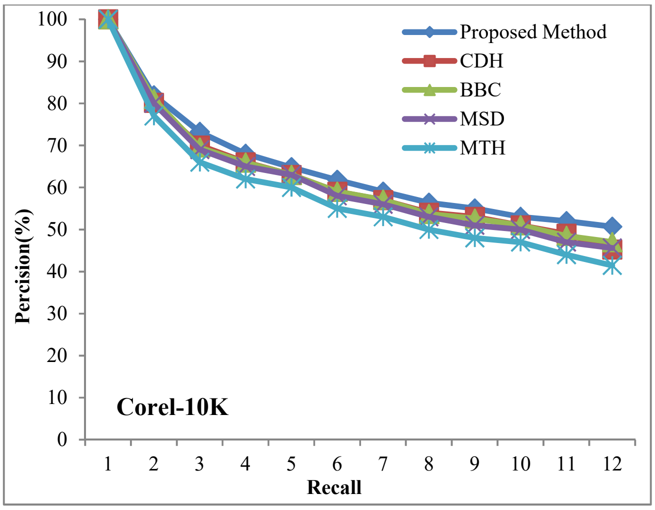
TABLE II
THE MAP AND MAR RETRIEVAL OF CDH AND COLOR HISTOGRAM BEFORE AND AFTER APPLY ENTROPY AND CORRELATION ON VALIDATION DATASET

Features	Performance	Before and After Application		
		First	Apply Entropy	Apply Correlation
CDH	MAP (%)	73.69	74.13	74.51
	MAR (%)	8.84	8.89	8.94
	N	164	71	61
Histogram	MAP (%)	52.7	52.73	52.84
	MAR (%)	6.32	6.32	6.34
	N	162	54	23

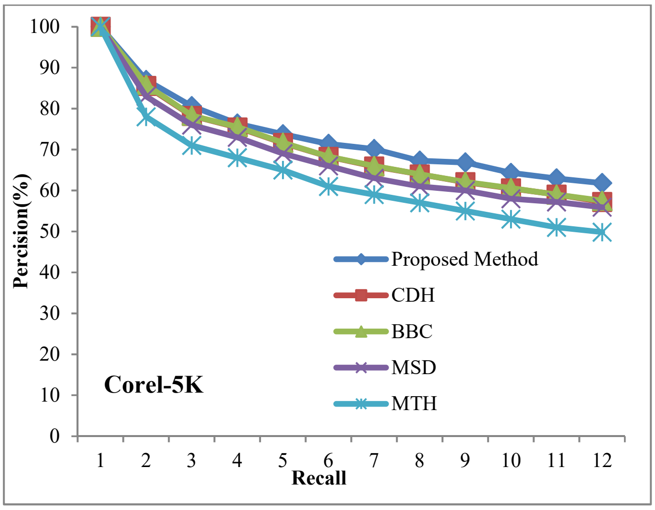
C. Performance Comparison of Various Approaches

In this section, the performance of the proposed method is compared with the more recently developed image retrieval methods. To compare the retrieval performance, precision and recall curves are used. In these curves, the horizontal axis corresponds to the recall and the vertical axis corresponds to the precision. The higher average precision and recall retrieval represents the higher performance of the method. These curves are plotted for each database separately.

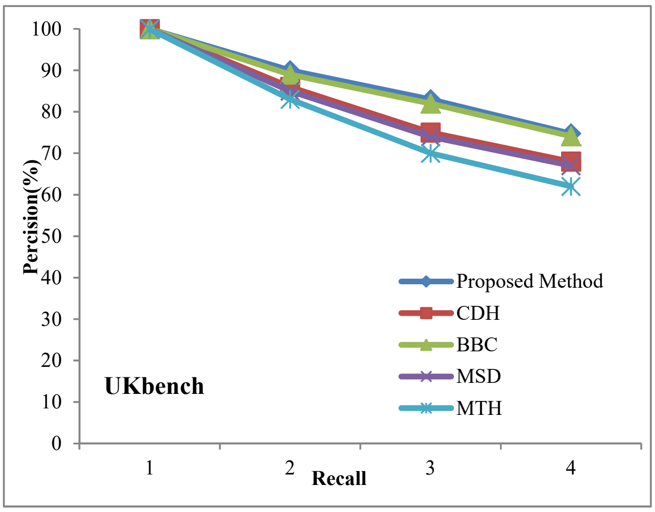
As mentioned earlier, the proposed method is compared with four methods including MSD [16], MTH [17], BBC [18] and CDH [19]. In these methods, to evaluate the retrieval system, 20% of the images are randomly used from Corel databases. In this paper, we randomly selected 20% of the images from each databases as query images. These images include all classes of image and do not share any image with the validation set.



(a)



(b)



(c)

Fig. 5 The precision and recall curves of the BBC, MSD, MTH, CDH and Proposed algorithms on: (a) Corel-10k, (b) Corel-5K and (c) UKBench datasets

TABLE III
THE AVERAGE RETRIEVAL PRECISION AND RECALL RESULTS USING THE THREE DATASETS

Databases	Performance	Methods				
		MTH	MSD	CDH	BDIP	Proposed
Corel-5k	P (%)	49.84	55.92	57.23	57.50	61.82
	R (%)	5.98	6.71	6.87	6.90	7.41
Corel-10k	P (%)	41.44	45.62	45.24	47.01	50.67
	R (%)	4.97	5.48	5.43	5.64	6.08
UKBench	P (%)	-	-	-	74.12	74.77
	R (%)				2.96	2.99

For the UKBench database, similar to the BBC method [18], the MAP criterion on the entire images of database is used. The results of average precision and recall are shown in Fig. 5 and Table III.

The results of the experiments show that the performance of the proposed method is better than other methods. It should be stressed that the proposed method performs well only by using a feature vector with the length of 84, whereas the vector lengths of the CDH and BBC [18] algorithms are 108 and 96, respectively, higher than that of the proposed algorithm. Only the feature vector length of the MTH and MSD algorithms are less than that of the proposed method.

Figs. 6 and 7 show two retrieval examples using the Corel 10K dataset. In Fig. 6, the query image is an image of a horse. All of the 12 retrieved images show valid matches in their texture, shape and color to the query image.

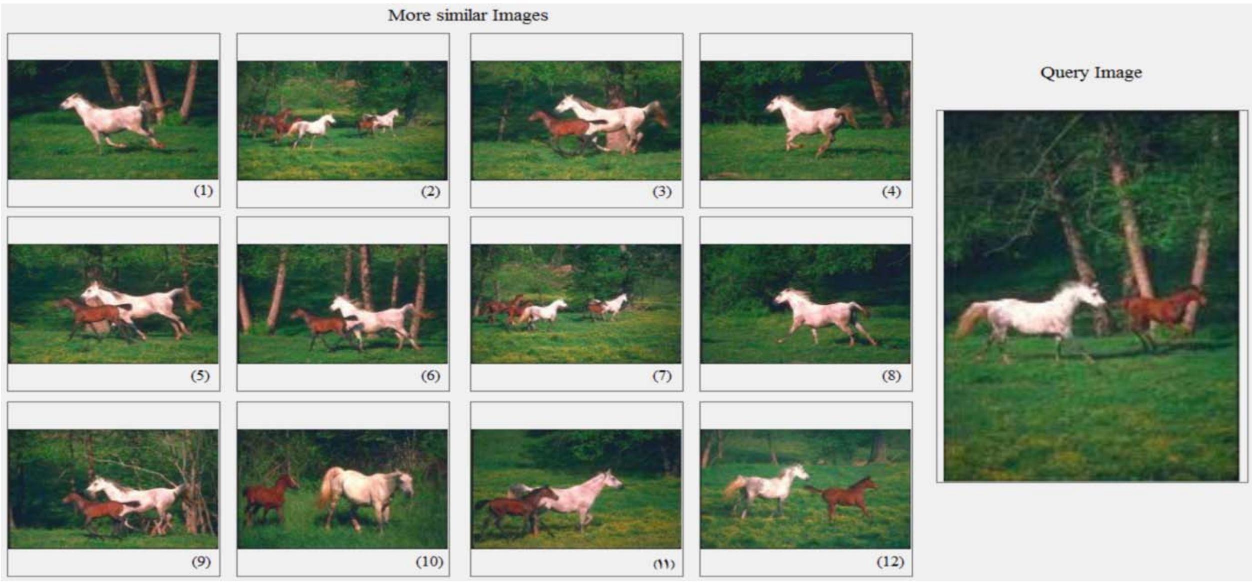


Fig. 6 An example of image retrieval using the proposed algorithm on the Corel 10K dataset. The query is an image of horses, and all the returned images are correctly retrieved and ranked within the top 12 images

In Fig. 7, the query image is an image of a car, and the top eight retrieved images show a valid match in texture, shape and color to the query image. In fact, images 9-12 do not belong to the query class but they have the vehicle concept.

In both retrieval samples, the query image searches among 10,000 images. So the proposed features in the HSV color space, extract semantic content of images with a high precision.

Another criterion to evaluate an image retrieval system is the retrieval time. The experimental results show that the image retrieval time of the proposed method compared with the MTH, MSD, CDH and the BBC methods has been improved too.

IV. CONCLUSION AND FUTURE WORK

In this paper, in order to reduce the semantic gap between the system perception and the human perception of an image, a new image retrieval system was introduced which used a combination of low-level features. On the other hand, the human visual system is very sensitive to color and edge orientation. Also, color histogram and CDH are two kinds of low-level statistics which are meaningful representatives of the image color and edge orientation information. Therefore in this paper, the low-level features were extracted from these two histograms.

In this paper, initially the superiority of the HSV color space to L*a*b* color space was discussed, and then the CDH features were extracted from this space. Also to improve color features, the color histogram in the HSV color space was added to CDH. Then by applying entropy and correlation methods to these features, 326 extracted features were reduced to 84 features. Finally, experiments on three different datasets showed that the proposed method in terms of accuracy of image retrieval is very efficient compared to the MTH, MSD, CDH and BBC [18] methods.

In the present analysis, we have used efficient and small feature vectors resulting in a high accuracy image retrieval system. In our future work, we will use the weighting of the features and use relevant feedback to obtain a more efficient image retrieval system.

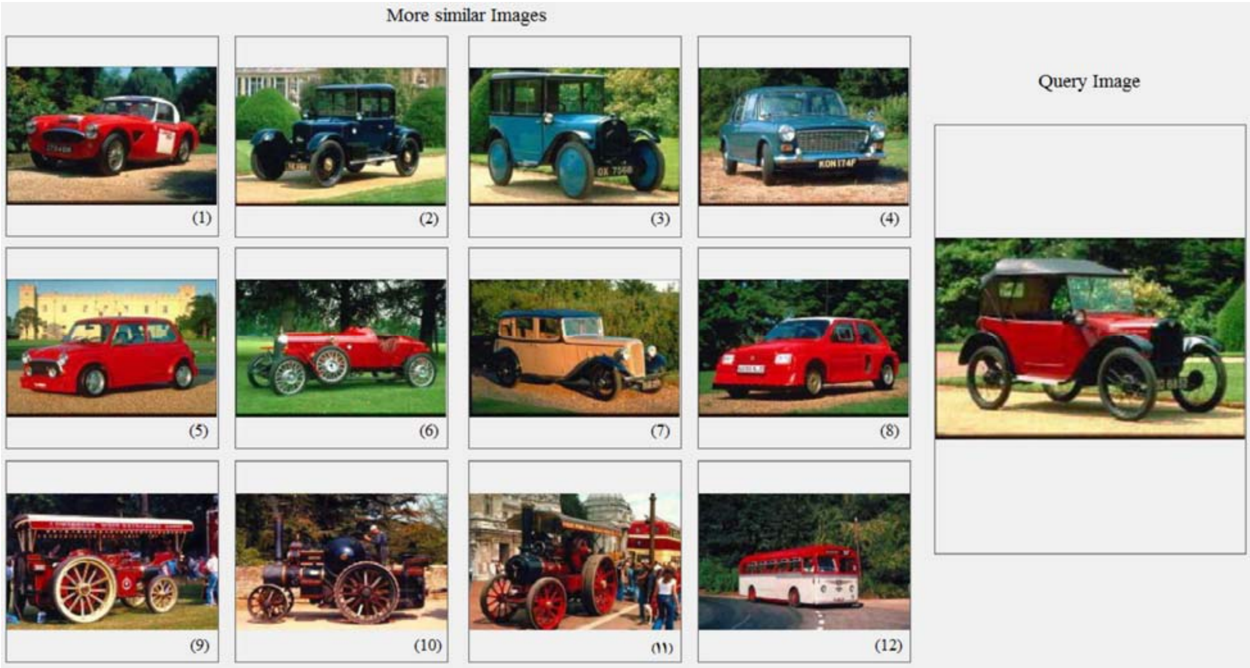


Fig. 7 An example of image retrieval using the proposed algorithm on the Corel 10K dataset; the query is an image of cars, and 8 images are correctly retrieved and ranked within the top 12 images

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