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FUSION OF COLOR AND STATISTIC FEATURES FOR ENHANCING CONTENT-BASED IMAGE RETRIEVAL SYSTEMS

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ABSTRACT

Content-based image retrieval is one of most debated topics in computer vision research, and has received a great deal of interest recently. It aims to retrieve similar images from a huge unlabelled image database. In this work we propose a method that reduces the error rate and retrieves relevant images early in the process, with the ability to work on both color and grayscale images. The proposed method scans an image using 8x8 overlapping blocks, extracting a set of probability density functions of the most discriminative statistical features. Our experiments, conducted on several image databases, show the robustness of the proposed method, outperforming some of the most popular methods described in the literature.
Keywords: *CBIR, Color Features, Statistical Features, Image Analysis, Computer Vision, Face Searching*.

1. INTRODUCTION

In recent years, attention to digital images has increased dramatically. Many websites and applications rely primarily on images such as Instagram [1], Facebook [2], etc. Search engines such yahoo contain a tremendous amount of images in their databases [3], making the virtual world swarm with a huge number of digital images. Typically, when searching for a specific image on these websites or on any database, textual descriptions of every image are needed [4] and these are normally located in the metadata to retrieve images similar to the query image [5].

However, the images may contain a huge amount of information [6], such information is difficult to be described in just a few words. So the description of each image in words is a tedious, expensive process and a waste of time and effort. Therefore, many strategies have been proposed in the literature to create a process for searching for an image based on the content of the searched images rather than on their annotation or textual description.

Content-based image retrieval (CBIR) has emerged as a new strategy to search for images [7] [8], particularly images with indefinite meanings, for example, medical, military, satellite and geographic images. Therefore, searching for images dependent on their content becomes more effective.

Recently, this area of research has gained great attention from researchers. Continuous improvement and evolving new techniques have made CBIR a growing research area [9].

A digital image is made up of a set of pixels. These pixels are associated with and related to each other, and appear in the image in the form of colors, shapes and objects, representing knowledge or a specific indication, which allows images to reflect their meaning. For example, the shapes and colors in vehicle images are different from those in mountains images. Objects and gradients in mountain images are different from those in sea images. This makes images belong to different groups, each group having its own general features, which are needed to distinguish them from other groups. However, some images from different groups share almost the same features and this makes CBIR a challenging task.

Many methods have been proposed to extract features from images [10]. Each has its own strengths and weaknesses. The more such methods become capable of describing the content of images, the better results CBIR achieves. Usually, more than one method for feature extraction is employed to obtain a variety of features, and this might lead to better results, but it might also have a negative impact on the overall speed of the retrieval process.

The goal of this study is to present new method for extracting features and representation of the image contents depending on a set of statistical features (Statistical dispersion, moments and measures of central tendency). The most discriminative features are used in this study, those features fused together in the feature level fusion as a set of probability density functions (PDFs). The new method presented for enhancing the performance of CBIR (in terms of precision and error rate ER). The reduction of the error rate helps in retrieving the relevant images early in the process,

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and this is critical and very important in CBIR systems. Many of method in CBIR field measure the performance using some of query images that randomly selected from datasets [11] [12], that will be unfair, because random choices of query image do not give a clear vision of the system performance. So in this paper all images in the datasets are used as query images, to give a clear vision of the system performance. Another important thing, that most of researcher in CBIR research papers evaluated their work using one dataset [11] [13] [14]. However, the proposed method tested and evaluated using more than one database. Also human faces database (ORL) used to show the ability of the proposed method to retrieve the similar face images.

The rest of this paper presents some of the most important work done in this area, discusses the proposed work, the evaluation methodology and the results of experiments that were conducted on different databases.

2. LITERATURE REVIEW

To solve the problem of CBIR, researchers have opted for a variety of approaches, such as color descriptors, color histogram, color correlogram [15] and color moment (CM) [10]. These are all widely used in CBIR applications. Usually images are full of color and these colors are considered a good descriptor of the content of the image. Usually images that carry the same colors show the same content or asymptotic content, but this does not always happen. Therefore most often another descriptor is used with color descriptors such: textures, shapes and other descriptors.

Huang and co-workers proposed a method for CBIR using color moment (CM) and Gabor Features. The combination of CM and Gabor Features was carried out for the purposes of obtaining more accurate results and speeding up the retrieval process. Huang and coworkers' experiments showed the accuracy of using color moment on both HSV and RGB color spaces; Euclidian distance was employed to measure the similarities between the query image and database images [16]. Gabor Features were also used by Manjunath and Ma for the CMIR problem [17].

Another use of color moment and Gabor Features was proposed by Mangijao and Hemachandran, who used HSV color space to represent image colors. The images were divided into three equal regions in a horizontal manner. For each region, the first three moments – mean, standard deviation, and skewness – were calculated and combined with a Gabor Feature. This process was executed on the H, S and V color channels of HSV color space. The Canberra distance [18] was used as a similarity measure. The result showed the performance of the retrieval process was computed on the first 10 retrieved images [19].

Singh and Hemachandran combined color histogram with color moment. HSV color space was used and the image colors were quantized to HSV (16, 4, 4) schema to make the process faster, with less storage space. The images were divided into three non-overlapping horizontal regions; three moments were computed for each color channel and combined with a 256-dimension histogram. Euclidean distance was used as a similarity measure to compute the difference between the query image feature vector and other vectors in the features database. This work shows experimentally how the combination of color moment and color histogram can improve the retrieval accuracy [20].

Another representation of image features was proposed by Liu and Yang, with a method called color difference histogram (CDH). The focus here is on the human visual system and how to represent image features perceptually by focusing on edge orientation. The process was carried out using L*a*b* color space, without any need for segmentation, learning or clustering methods. The difference between vectors was computed using Canberra distance. Their experiments used 20 images as query images, which were selected randomly from each category of the database used [21].

Vatamanu and coworkers proposed a method using local binary patterns (LBP) to describe image content and they then compared the results with color Histogram and color Coherence Vector (CCV). They used the Weka tool [22] and K mean clustering with Naive Bayes for classification [23]. In the CBIR field the image class is not known (unlabeled data), and therefore, we cannot use traditional supervised learning methods [24].

Local binary pattern and local ternary pattern are used as robust texture descriptors. A novel method called Color Directional Local Quinary Pattern (CDLQP) was proposed by Vipparthi and Nagar. This method works by detecting the directional edge obtained from red, green and blue colors separately, and four directions: 0, 45, 90 and 135 are calculated. Then the histogram for each color is constructed, and the feature vector is obtained from the histograms [25].

Agarwal and co-workers proposed an algorithm based on more than one descriptor for feature extraction. Edges were detected using Canny edge detection [26] on the Y matrix of the YCbCr color space after converting it from RGB. This was very useful in eliminating the problem of color variation in RGB color space. After the edge detection process

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on Y being merged with Cr and Cb again, the RGB color space is obtained again from the new YCbCr. After that, discrete wavelet transform (DWT) is applied on the histograms of the red, green and blue channels with different levels to obtain a feature vector with 128 features; Manhattan distance is employed as a similarity measure. To test their work, they randomly selected 5 images from the database to be used as query images [11].

Another use of colors as a descriptor of the content of images appears in the work of Lande and coworkers, where the color features were combined with other features such as shape and texture to make the process of content description more efficient. This work focused on the dominant color in each block in the image, after dividing it into a number of non-overlapping blocks. The dominant color is determined by using a K-means clustering algorithm. Texture features are extracted using grey level co-occurrence matrix. Fourier descriptor is applied on the segmented image for a better description of the shapes and objects. The combination of these features enhanced the performance of the proposed system [27].

Motifs and differences between pixels of a scan pattern (DBPSP) and color co-occurrence matrix (CCM) are efficient techniques to use as texture and color descriptors in CBIR systems. Lin and coworkers proposed using both CCM and DBPSP. The CCM traverses images used 3*3 convolution mask, the values in this mask were divided into four 2*2 blocks, and 7 of the scan patterns were extracted from each one. The differences between pixels in the scan pattern were calculated and converted into the probability of occurrence of pixels in the images using DBPSP. They also used another feature, the color histogram for k-means, where all pixels of the images database were clustered using k-mean clustering to divide these pixels into 16 groups to get 16 (color histograms for K-mean) (CHKM) features. Their experimental results showed that the proposed features can offer an efficient description of image content [28].

ElAlami used CCM and DBPSP again in the same manner as in [28], except that the similarity measured by the novel matching method was dependent on the so-called mini-mum area between two vectors. The vectors were represented as a nonlinear regression function, and the areas between the query image vector and all the other vectors represent the distances. Artificial neural network (ANN) and dimensionality reduction technique were used in this work. The experiments showed the performance of the matching method on different databases [12].

We think that the randomly selected images as query images by a large number of researchers offers a biased evaluation of CBIR, as we cannot predict the images and/or the categories searched for in a real application. This is one of the serious problems associated with CBIR studies, particularly when it comes to the evaluation of the proposed work. Some researchers [29] [30] [31] [32] attempted to use less bias and standard evaluation techniques such as precision, average precision (AP), mean average precision (MAP) and error rate (ER).

The use of all images in the database as a query image (leave-one-out cross validation) gives a clearer perception of the performance of the system proposed. This approach will not take a long time, because the features are extracted to all images (once) forming a feature database instead of an image database, and if those features are indexed the process will be much faster.

3. THE PROPOSED WORK

Basically, color moments alone are not enough to represent the content of images [10]. In most research papers the first three moments are used to represent the colors in the image. These values are mean, variance, and skewness [16]. The reason behind the lack of accuracy using these values in CBIR is the way in which these values are calculated. Usually these values are computed on each matrix of color space [20], for example RGB or HSV. Each channel of RGB has a huge number of values, for example, if the image size is 200×200 there will be 40,000 values for each matrix. Thus many different images using these values may give the same features; e.g. the mean of the values (10, 40, 60, and 10) and (32, 28, 31and 29) is 30 for both, despite them having different colors and perhaps different shapes if there is a large number of values as in the case of images.

Therefore, we propose another way of computing color moment and statistical values for images. Basically, when an image is divided into small blocks or regions, the effect of permutation of values (different values give same result) will be reduced, because the values in a small block are more likely to describe the related shape or object shown in that block. Overlapping blocks seem to be more efficient in describing the correlation of values of each block with neighboring blocks. After the division of image into small blocks, the moments and some other features are extracted from each block.

A vector is needed to represent each one of the features that are extracted from each block. For example:

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$$\mu = [\mu_1, \quad \mu_2, \quad \ldots, \quad \mu_n]$$
$$\sigma = [\sigma_1, \quad \sigma_2, \quad \ldots, \quad \sigma_n]$$

where μ represents the mean vector, μ_1 is the mean extracted from the first block, μ_2 is the mean extracted from the second block, and so on. Binning is used for each vector to group the values into small intervals (histogram). The probability density function (PDF) is then created based on the histogram values. This step makes vectors or PDFs invariant to scale and rotation of images (as will be shown in the experiments). Finally, the PDFs are concatenated to create one discrimin-ative feature vector for each image. Figure (1) represents the block diagram of the proposed system.

As can be seen from the block diagram, we can use this work on either grayscale or colored images. This is better than the color histograms if we need to deal with grayscale images such as ultrasound and other medical images.

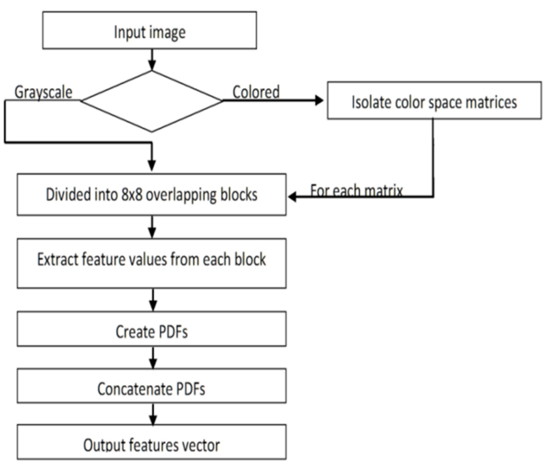

Figure 1: The Block Diagram Of The Proposed System.

Figure 2 shows how the image divided into 8×8 overlapping blocks. In the experiments section we will show how the performance affected with block size, color model and number of bins used.

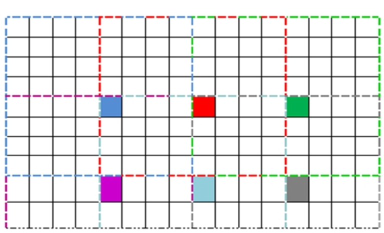

Figure 2: The Division Of An Image Using 8×8 Overlapping Blocks.

The Mode and the Median are calculated from each block, in addition to some other popular and discriminative features, including:

Mean $$\mu_i = \frac{1}{N}\sum_{j}^{N} V_{(i,j)} \quad (1)$$

Standard deviation $$\sigma_i = \left(\frac{1}{N}\sum_{j}^{N}\left(V_{(i,j)} - \mu_i\right)^2\right)^{\frac{1}{2}} \quad (2)$$

Skewness $$\gamma_i = \left(\frac{1}{N}\sum_{j}^{N}\left(V_{(i,j)} - \mu_i\right)^3\right)^{\frac{1}{3}} \quad (3)$$

Kurtosis $$k_i = \left(\frac{1}{N}\sum_{j}^{N}\left(V_{(i,j)} - \mu_i\right)^4\right)^{\frac{1}{4}} \quad (4)$$

Entropy $$E_i = -\sum_{i}^{m}\sum_{j}^{n} p(i,j)\log(p(i,j)) \quad (5)$$

–where $v(i,j)$ is the pixel value and $p(i,j)$ is the probability of that value. The Discrete cosine transform (DCT) is also calculated, taking the first 3 zigzag values from each block. For example, the DCT vector for the red matrix of RGB color space is:

$$DCT_{Red}: DCT_{11} \quad DCT_{12} \quad DCT_{13} \quad DCT_{21}\ DCT_{22} DCT_{23} \ldots DCT_{N3}$$

–where DCT_1 is the first zigzag value (DC) from the first block, DCT_1 is the second zigzag value from the first block etc, and N is the number of blocks.

The values are scaled to the range [0, 20] to eliminate negative values; one PDF is created with 20 bins for each matrix. It is worth mentioning that the work of [33] showed that using DCT is efficient for CBIR.

In our experiments, the DCT features are extracted from RGB color space, and then combined with other statistical features that are extracted from HSV in the case of color images, obtaining one feature vector, which contains 270 attributes for colored images, and 90 values for grayscale images (see Figure (3)).

Method	Mean	Mean	Mean	Mode	Mode	Mode	...	DCT	DCT	DCT
Color matrix	H	S	V	H	S	V	...	R	G	B
# bins	10	10	10	10	10	10	...	20	20	20

Figure 3: The Final Feature vector.

Discrete cosine transform theory is discussed in [34] and the following equation represents DCT in two dimensions, where A_m is the input image and B_p is the output image.

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$$B_p \;= a_p a_q \sum_{m=0}^{M-1}\sum_{n=0}^{N-1} A_m \; c \; \frac{\pi(2m+1)p}{2M} \; c \; \frac{\pi(2n+1)q}{2N}, \quad \begin{matrix} 0\le P\le M-1 \\ 0\le q\le N-1 \end{matrix} \qquad (6)$$

Where

$$a_p = \begin{cases} \frac{1}{\sqrt{M}}, & P = 0 \\ \sqrt{\frac{2}{M}}, & 1 \le P \le M-1 \end{cases} \quad \text{and } a_q = \begin{cases} \frac{1}{\sqrt{N}}, & q = 0 \\ \sqrt{\frac{2}{N}}, & 1 \le q \le N-1 \end{cases}$$

The discriminative power of the proposed method can be noticed in Figure (4), which demonstrates the discriminative power of the Mean PDF of the Hue values, the almost Similar PDFs within each class and different PDFs between classes.

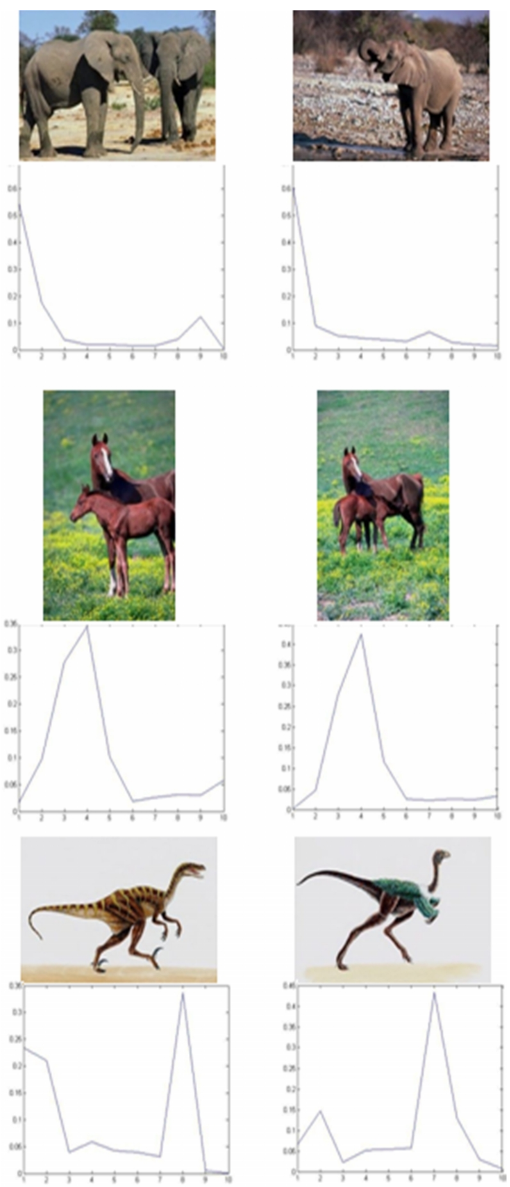

Figure 4: Examples For Pdfs Calculated Using The Mean Of Hue From HSV Color Model.

4. CBIR EVALUATION METHODS

The evaluation of CBIR systems is a critical problem in this field. There are many techniques to measure the accuracy and the performance of the systems. The lack of standardization and each researcher choosing a different evaluation method makes it difficult to compare the performance of CBIR methods. Therefore, we should maintain standardization methods for evaluating research and systems in this emerging and rapidly growing field of research.

The most common methods for evaluating CBIR systems are precision and recall, precision is defined by the number of retrieved images relevant to the query image divided by the total number of images retrieved, and recall is defined by the number of retrieved images relevant to the query image divided by the total number of relevant images in the database.

The precision can be calculated at any point of a retrieved image. Considering this point as the number of images that the system will retrieve, P(N) is called precision at N, where N is the number of image retrieved; P(1) represents the precision after the first retrieved image, P(2) after the second retrieved image and so on.

There are also two other methods for evaluating CBIR, which are also derived from precision and recall: the average precision (AP) and mean average precision (MAP). AP refers to the average of the precision scores after each retrieved relevant item for a single query, while the MAP is the average of AP for a certain number of queries:

$$A_q = \frac{1}{N_R}\sum_{n=1}^{N_R} P_q(R_n) \qquad (7)$$

$$M = \frac{1}{|N|}\sum_{n=1}^{N} A_q \qquad (8)$$

where R_n is the recall after the n_{th} relevant image was retrieved. N_R is the number of relevant image and N is the number of queries. AP is approximately equal the area under precision-recall curve [35].

Error rate (ER) is also used to measure the performance of CBIR systems. Generally it can be

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calculated by dividing the number of retrieved images not relevant to the query image by the total number of images retrieved.

ER is one of the most useful measures for evaluating CBIR. Less error rate means that the relevant images are retrieved early (e.g. the first retrieved image). The retrieval of a relevant image early is critical and important for CBIR systems.

In this work we evaluate the proposed system using both AP and MAP, because they offer a clear vision for the system performance. The error rate used in our experiments is calculated using:

$$ER = 1 - P(1) \quad (9)$$

where P(1) is precision after the first image is retrieved. We used equation (9) to compare the performance of the proposed system with the most popular methods that were evaluated in [29].

The precision shows the average of precision after each image is retrieved using the proposed system for all images in the databases used. We think that AP, MAP and Error rate are the best measures to be used by other researchers to standardize evaluation of CBIR systems and methods. Moreover, instead of testing just a small random number of images, all images should be considered as query images, so as to make systems more comparable in terms of performance.

Figure 5: Sample Images From Wang Database.

5. RESULTS AND DISCUSSIONS

To evaluate the proposed system, several experiments were conducted using 4 databases; the description of those is shown in Table (1). All the experiments were implemented using Matlab2014b.

Table 2: MAP And ER Of The Proposed System Compared To Other Methods Reported In [29].

Database	**Wang**	
Method	**ER[%]**	**MAP[%]**
Proposed	**16.3**	**39.4**
Color histogram	16.9	50.5
LF SIFT global search	37.2	38.3
LF patches histogram	17.9	48.3
LF SIFT histogram	25.6	48.2
inv. feature histogram (monomial)	19.2	47.6
MPEG7: scalable color	25.1	46.7
LF patches signature	24.3	40.4
Gabor histogram	30.5	41.3
32x32 image	47.2	37.6
MPEG7: color layout	35.4	41.8
Xx32 image	55.9	24.3
Tamura texture histogram	28.4	38.2
LF SIFT signature	35.1	36.7
gray value histogram	45.3	31.7
LF patches global	42.9	30.5
MPEG7: edge histogram	32.8	40.8
inv. feature histogram (relational)	38.3	34.9
Gabor vector	65.5	23.7
global texture feature	51.4	26.3

Table 1: Description Of Databases Used To Evaluate The Proposed System

Database	Images	Queries	Avg. relevant
Wang [36]	*1000*	*1000*	*99*
Coil-100 [37]	*7200*	*7200*	*71*
AT&T (ORL) [38]	*400*	*400*	*9*

We used Hassanat distance (HD) [39] as a similarity measure, because it is claimed to be robust to noise and outliers, which are both critical when dealing with CBIR systems. Moreover, the preliminary results of our pilot study showed that the performance of the system using HD outperforms those when using other distances such as the Euclidian and Manhattan. HD for positive numbers is calculated as:

$$H \ (A,B) = \sum_{i=1}^{m}\left(1 - \frac{1+m\ \mathrm{n}(A_i,B_i)}{1+\mathrm{m}\ \ (A_i,B_i)}\right) \quad (10)$$

where A_i is the ith value in vector A and B_i is the ith value in vector B. The performance of the proposed method on Wang database was compared with some of the most popular methods that are

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currently used in the CBIR field. Those methods were tested and reported by [29], and the comparative results are shown in Table (2). Some sample images from Wang database are shown in Figure (5).

As can be seen from Table (2), the perform-ance of the proposed system outperforms most of the methods mentioned in the same table. Obviously the results are much better for the Wang database (in term of ER) and outperform all the features that used in the same table.

The performance of the proposed work was also compared with the work of [11] using the Wang database. Figure (6) shows the precision after each point of retrieving images.

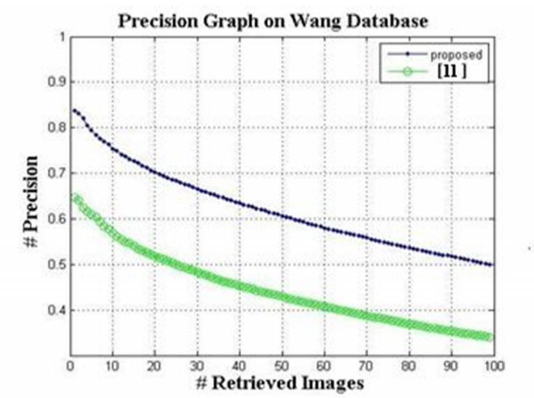

Figure 6: The Performance Of Proposed System Compared With [11] On Wang Database.

A query example from the Wang database demonstrated in Figure (7) showing the first 12 relevant images that were retrieved by the proposed system.

Figure 7: The Images Retrieved For A Query Image Example Using The Proposed System.

Coil-100 database contains 7200 images for 100 different objects, with 72 images for each object, with different scales and rotations. Some sample images from the Coil-100 database are shown in Figure (8).

Figure 8: Sample Images From Coil-100 Database.

The performance of the proposed method compared to the method proposed in [11] is illustrated by Figure (9), and the precision is depicted after each image retrieved. As can be seen from the same figure, the proposed method reduced the error rate dramatically to 0.0021, which means that relevant images are retrieved very early.

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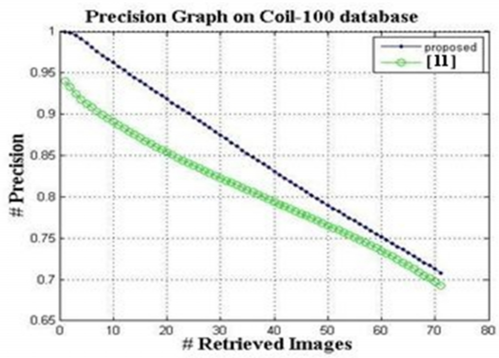

Figure 9: The Performance Of The Proposed System Compared With [11] *On Coil-100 Database*

Figure 12: The Results Of Querying Process Using An Image From ORL Database.

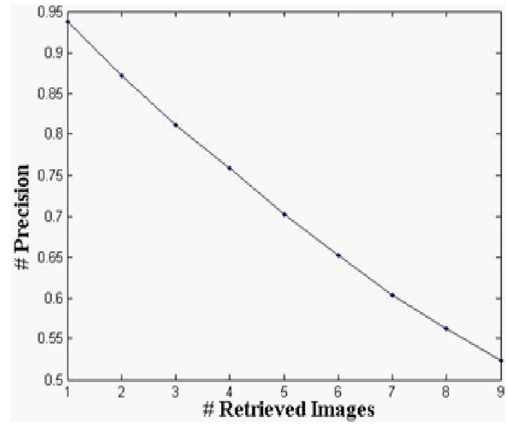

Figure 11: The Performance Of The Proposed System On ORL Database.

The proposed method was also applied on the ORL face database, which contains 400 images for 40 subjects, with 10 images for each subject. Sample images from the ORL face database are shown in Figure (10).

Figure 10: Sample images from ORL database.

The precision graph for the performance of the proposed method on the ORL database is depicted by Figure (11). The error rate using this database is 0.12, which means that the average precision of the first image retrieved is 0.88. This experiment proves that it is possible to use the proposed method to identify a person from their face, if it is used with a search engine; the retrieved images retrieve their URLs, and the website containing the image, typically the name and identity of a person, are associated with their image.

Figure (12) shows visual example about using an image from ORL database and the results of the query process.

As stated previously, using PDFs to represent feature makes those features invariant to scale and rotation of images. Preliminary results suggest that the rotation and resizing of images do not change the extracted features significantly, because those features are based on the probabilities of the measures used; ideally, the probability (of the pixel

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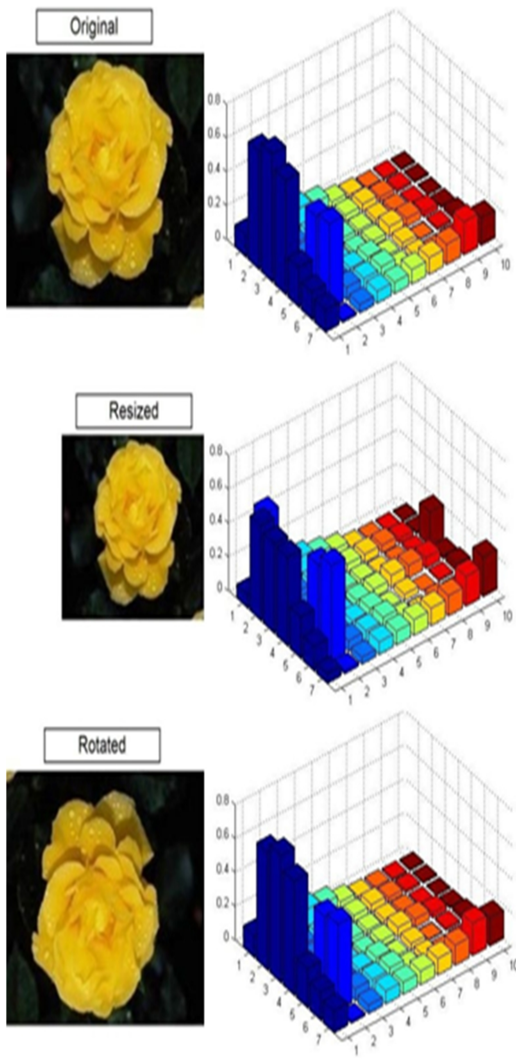

Figure 13: The Effect Of Scale And Rotation On The 7 Proposed Pdfs Of The Hue Matrix.

The performance measures MAP and ER of the proposed work on the four datasets used are summarized in Table (3).

Table 3: Summary Of The Performance Of The Proposed System On Three Datasets.

Database	ER	MAP
Wang	0.163	0.394
Coil-100	0.001	0.679
ORL	0.062	0.485

The previous results in general show how the proposed system reduces the error rate dramatically on colored images; however, less accuracy is achieved on grayscale images due to the lack of color information.

values for instance) is not affected by translation, rotation or scale. Figure (13) shows that 7 PDFs of the Hue matrix (of an image, scaled down and then flipped) are almost similar, with some minor differences. This indicates that the performance of the proposed system is not affected by the size or the rotation of the query image significantly.

A new set of experiments was conducted to show how the use of a different number of bins, different size of blocks and the color space used affect the results. In these experiments, the first 10 images from each category of the Wang database were used to obtain a new small dataset with 100 images.

Figure (14) shows the precision with different numbers of retrieved images using different numbers of bins. (10,10) in the figure means 10 bins for statistical features and 10 for DCT features respectively. (HSV, RGB) means that the statistical features extracted using HSV color model and the DCT features extracted using RGB color model respectively, and so on.

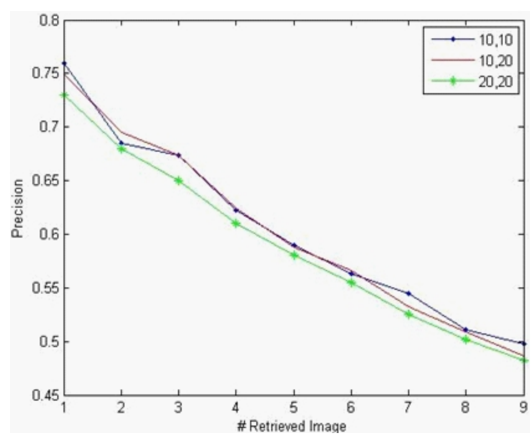

Figure 14: The Performance At Different Numbers Of Retrieved Images Using Different Numbers Of Bins.

In Figure (14) the block size is 8x8 and the color spaces are HSV for statistical features and RGB for DCT. Figure (15) shows the effect of color model of the final results of precision.

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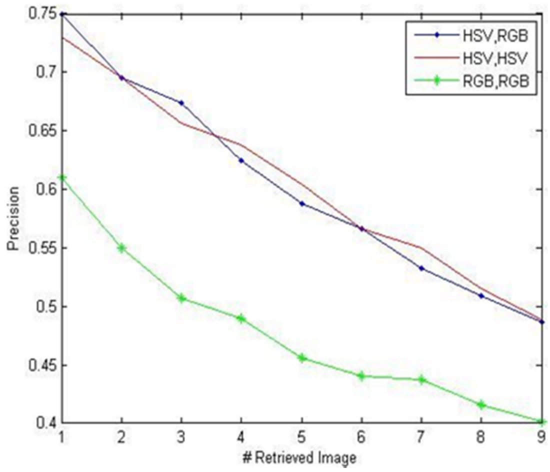

Figure 15: The Performance At Different Numbers Of Retrieved Images Using Different Color Spaces.

Figure (15) shows the precision using different color spaces where the bins are 10 for statistical features and 20 for DCT where the block size was 8×8.

Figure (16) shows the how the block size also affects the performance (precision) of the proposed system.

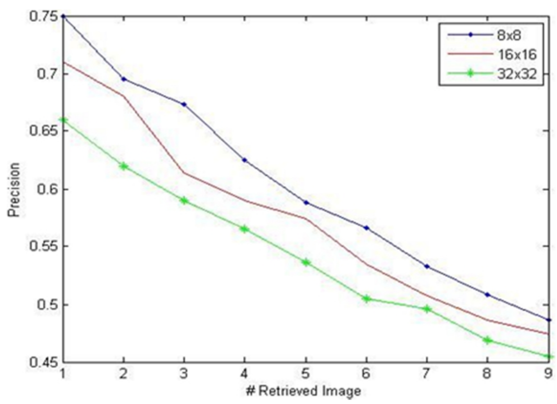

Figure 16: The Performance At Different Numbers Of Retrieved Images Using Different Block Sizes.

Finally, Figure (16) shows the precision using different block sizes where the bins are 10 for statistical features and 20 for DCT and the color spaces are HSV for statistical features and RGB for DCT.

In our experiments on the full database of 1000 images (Wang) the proposed method achieved the best accuracy by using 10 bins for statistical features and 20 bins for DCT, where the color spaces were HSV for statistical features and RGB for DCT with 8x8 as the block size.

6. CONCLUSION

In this paper, a new approach to CBIR is proposed. The new method works by scanning the image by 8x8 overlapping blocks and extracting some discriminative statistical features from each block. These are then used to create a set of probability density functions PDFs, which are fused in the feature level, forming one feature vector for each image. We found that the features used reduced the error rate and retrieved the relevant image early (first or second retrieved image is relevant to the query image), which is very important and critical for CBIR systems.

The experiments show that the proposed method works well on color images, and outperforms several other methods proposed in the literature. We are planning to extend our work employing other features such as gradient and motifs, focusing on the shape information rather than just texture features without paying attention to the largest segmented object in a scene (the subject of the image). In addition, special attention will be given to the face retrieval system, taking into account more related features that strongly identify persons, such as the inner facial features. These enhancements and more will be left to be conducted in the future.

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