Content Based Image Retrieval using Color Histogram and Discrete Cosine Transform

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Abstract — *This paper proposed a color image retrieval approach based on images' content. This approach is based on extracting an efficient combination of low visual features in the image; color and texture. To extract the color feature, color histogram was used, where the RGB color space was converted into HSV color space, then the color histogram of each space was taken. To extract the texture feature, DCT transformation was used, and DC coefficients are taken meanwhile neglecting AC coefficients. The experimental results were analyzed on the basis of three similarity measures, Manhattan Distance , Euclidean Distance and Mean Square Error. MD similarity measure proved its efficiency in retrieval process compared with other similarity measures at both the execution time and retrieval accuracy. The accuracy and efficiency of the system were evaluated using the precision and recall metrics. The results obtained from the proposed approach showed good results when considering precision measure in evaluation process. The precision was increased by (8.3%) rate compared to the best result of previous studies.*

Keywords — *Image Retrieval, Content-Based Image Retrieval, Color Histogram, Discrete Cosine Transform.*

I. INTRODUCTION

In recent years, large collection of digital images have been created and dramatically increased, this includes many academic areas, trade/business, government sectors, medical applications, and traffic control. Technology has played a major role in many inventions, such as photography and television, which has facilitated the capturing and transferring of image data. The computer is the main engine of the revolution of photography, many technologies and devices that brought with it for capturing, processing, storing and transferring images.

A huge amount of digital images become accessible to the public usage. However, we may not be able to get benefit from them unless the review, inquiry, search and recovery process is efficient. The main problem is the difficulty of identifying the desired image in a large variety of image data set. While it is very practical and it is possible to select the desired image from a small set of images as soon as browsing, more effective techniques are needed with large sets of digital images[1].

Image retrieval is one of the most important areas of research among researchers in the field of image processing. Researchers are focusing on new ways by which images can be easily, quickly and accurately retrieved and accessed from large databases. The retrieval mechanism and processing of the desired image from the database are important. At early stage, a major focus was placed on the process of retrieving images in what is now known as Text-Based Image Retrieval (TBIR), also known as concept based image retrieval[2].

Retrieving images based on TBIR with a small database is a straightforward way method. But the drawback of it is a manual suspension, impossible and expensive task for a large database[3].

The methods used to retrieve images using text search techniques may suffer from inconsistencies between text and visual content if visual content is ignored as a classification guide. Attract Content-Based Image Retrieval (CBIR) which depends on identifying relevant images on visual content representation has been a constant concern in the past two decades[4].

Many content-based technologies have been developed in the last decade. CBIR is a field and a set of technology algorithms that enable the user to query the image databases using image content such as color, texture, and shape without using text attributes such as image name or other keywords.

This paper presents an image retrieval approach based on the color histogram and DCT techniques to extract image's information according to the color and texture features of the retrieved images, to enhance the efficiency of CBIR systems in terms of the accuracy of retrieved data.

The remainder of this paper is structured as follows: In section II, the extraction and representation of image features is described. Section III describes the feature similarity measurements used in this study. Section IV presents the related works regarding to CBIR. Section V describes the architecture of the proposed approach. Section VI discusses the evaluation of the proposed approach, and the obtained results. The last section presents the conclusion of this research work.

II. IMAGE FEATURES

The feature can be defined as capturing a specific visual property of an image. In general, image features can be global or local. Global features describe the visual content of the entire image, where local features describe areas or objects of the image content. The features are used as a starting point for many computer vision algorithms. Because features are used as a starting point and basic priorities for the algorithms, the general algorithm is often only as good as the feature detector[2].

A. Features Extraction

Extracting image feature means getting useful information that can describe the image with its content. Objects in the image can be considered as shapes that can be an advantage of the image. To describe the image, we must consider its main features[5]. The importance of features extraction in image engines is very obvious. It helps in finding or search matching features from the database. The visual features that CBIR trusts including shape, semantic elements, structure, texture and color[6].

B. Color Histogram

One of the most visible and visual features of the image is color, it is the basic feature of the image contents because the human eye is sensitive to it and can recognize the images and objects contained in the image using color features. The color histogram (CH) is used to describe and represent colors in the image, which displays the pixel ratio of each color within the image[5]. In CBIR systems, the color histogram is used more frequently to calculate the distance criteria based on the chromatic similarity of each image, given its features such as high efficiency[2].

C. Discrete Cosine Transform

There are many mathematical transforms that are used in texture representation. The discrete cosine transform (DCT) is remarked to be the best in image power compression in very few conversion coefficients. DCT has been widely used for efficient texture feature extraction. DCT helps in separating the image into parts of differing importance (with respect to the image's visual quality). The DCT is similar to the discrete Fourier transform, it transforms a signal or image from the spatial domain to the frequency domain[7]. For example, an image is a two-dimensional signal that is perceived by the human visual system. The DCT Transformation can be used to convert the spatial information into numeric data (frequency or spectral information), where the image's information exists in a quantitative form (coefficients) that can be manipulated. In the literature the DCT has been widely used for efficient texture feature extraction[8].

In sake of efficient texture feature extraction, some DCT coefficients are used in the compressed domain as the feature vectors[9]. The DCT coefficients are acquired covering different spectral bands, to gain a fast feature extraction for the compressed domain. For texture images, much of the signal energy lies at low frequency components, which appear in the upper left corner of the DCT[10].

The DCT decomposes the signal into underlying spatial frequencies, which then allow further processing techniques to reduce the precision of the DCT coefficients consistent with the Human Visual System (HVS) model. The DCT coefficients of an image tend themselves as a new feature, which has the ability to represent the regularity, complexity and some texture features of an image and it can be directly applied to entire image data or to sub-image of various sizes in the compressed domain[9].

III. FEATURE SIMILARITY MEASUREMENT

Measurement of similarity is the process of approximation of the solution, based on the calculation of the function of the similarity between a pair of images. The result is a set of possible values. Once the database features are created, the user can give an image as input to the application to retrieve similar images from the database. To calculate the similarity or congruence between the input query image and the database image, the difference between the feature vector of the query image and the vector of the database image is calculated using different distance metrics, such as Euclidean Distance (ED) and Manhattan Distance (MD)[11, 12]. Measuring similarity is another important issue in CBIR where the query image is compared with other database images for similarity.

A. Manhattan Distance (MD)

The Manhattan distance, also known as rectilinear distance, or city block distance. Manhattan Distance between two points is the sum of the absolute differences of their coordinates. The Manhattan Distance is shown in Equation (1).

$$MD_{(x,y)} = \sum_{i=1}^{n} |x_i - y_i| \qquad (1)$$

Where n is the number of variables in each vector, $\boldsymbol{i}$ denotes the range 1....$\boldsymbol{N}$, and $\boldsymbol{x}_i$ and $\boldsymbol{y}_i$ are the values of the $\boldsymbol{i}^{th}$ variable, at points $\boldsymbol{x}$ and $\boldsymbol{y}$ respectively[13].

B. Euclidean Distance (ED)

Because of its efficiency and effectiveness, Euclidean Distance metric is the most widely used for similarity measurement in image retrieval. It measures the distance between two vectors by computing the square root of the sum of the squared absolute differences, its shown in Equation (2)[12].

$$ED_{(x,y)} = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2} \qquad (2)$$

Where ***ED*** is the distance between two vectors ***x,y*** and ***n*** represent the number of values in each vector, ***i*** denotes the range 1....***N***, and ***xi*** and ***yi*** are the values of the i^{th} variable, at points ***x*** and ***y*** respectively.

C. Mean Square Error (MSE)

MSE measures the average of the squares of the errors that is, the average squared difference between the estimated values and what is estimated. MSE is always non-negative, and the smaller value of the MSE represents the better result. It is calculated as in Equation (3).

$$MSE_{(x,y)} = \frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2 \qquad (3)$$

Where $\boldsymbol{x}$ and $\boldsymbol{y}$ can be any arrays of any dimension, but must be of the same size $\boldsymbol{n}$[14].

IV. RELATED WORK

Several academic works have been done in the last view years related to CBIR. However, the most relevant studies for our approach are discussed in this section.

A. Query by Color Content

Mohammed and Dawood in[15], suggested three ways to retrieve image, all of them depending on color histogram. In a color histogram method, the histogram is divided into sub-block histogram with 17 blocks, each block contains 15 grayscale colors for each of the RGB component of each image read from the database. In a Prime value method of color histogram, the frequency of the primes number between 0-255 is taken for all images in database and query image for each color (R, G and B). In color moment method, the histogram value for three band (R, G and B) computes the set of moment (Mean , Entropy , Variance and Standard Deviation) of the color image for each band and applying the measurement distance. Experiment results show that the Prime algorithm is relatively easy, and it is effective among the other three techniques.

The authors in[16] presented an effective image retrieval method which is based on the color feature. Three dimension color space HSV is used and a (16:4:4) non-uniform quantization method is adopted in which H vector is divided into 16 values and S, V is divided into 4 values separately. The Minkowski distance is used to compare only the same bins between color histograms. For training purpose, almost 700 images have been used. For each image, a 3-D histogram of its HSV values is computed. At the end of the training stage, all 3D HSV histograms are stored in the same file. The average of retrieval time was four seconds which is very fast.

B. Query by Texture Content

In[17], Hemalath Proposed a method that uses the shape as a feature to be extracted from (Statistical Region Merging) SRM algorithm and from DCT. The three feature databases are extracted as edge images using SRM and DCT and the DCT images itself. Feature databases are considered from three different processing of the query image. The first feature database is considered from the border images extracted using SRM. The second feature database is generated by applying DCT on the query image, and the third feature database is generated by obtaining the edge images from DCT by using Sobel in Black and White images. The similarity measurement is given by RGB projection which determines the size of the image and compares the images in the database with the query image. The proposed work contributed much towards the accuracy by treating the images in three different feature databases.

The researchers in[18], presented two grading retrieval algorithms based on DCT compressed domain and DWT compressed domain. The work is conducted on three stages: The first level, feature vector is obtained by using the mean and standard deviation of low-frequency information as the texture feature vector. In the second level, the features are extracted from high frequency of wavelet sub-bands which describes the details of images. In the third level, in order to improve retrieval accuracy, they use fast wavelet histogram techniques to construct wavelet histogram to describe texture feature of images further. The results show clearly that two grading image retrieval algorithms work better than other algorithms.

C. Query by Color and Texture Content

Another study in[19], presented a novel approach to extract the texture and features of an image. A feature descriptor obtained from a color image is constructed from the EDBTC encoded data by incorporating the Vector Quantization (VQ). The two methods introduced are Color Histogram Feature (CHF) and Bit Pattern Histogram Feature. The CHF effectively represents the color distribution within an image, while the Bit Pattern Histogram Feature (BHF) characterizes the image edge and texture. Experimental result shows, the proposed indexing method outperforms the former BTC-based image indexing and the other existing image retrieval schemes with natural and textural datasets.

In[20], the researchers proposed a new CBIR technique to fuse color and texture features. Color Histogram (CH) is used to extract a color information. Texture features are extracted by DWT and Edge Histogram Descriptor (EDH). First, it must apply a low pass filter to preserve the low frequency and high pass filter to preserve the high frequency of an image. Then, applying four level DWT to image and construct a feature vector for the first two moments those are the mean and standard deviation. Finally, the feature vector is constructed by Edge Histogram Descriptor (EHD). Query image is taken and the previous steps are repeated to build a feature vector based on color and texture feature. The distance between the query image and database image is calculated using Manhattan distance. The experimental results show that, the proposed method outperforms the existing CBIR systems.

V. PROPOSED APPROACH

This section presents the proposed method of color images retrieval system based on color histogram and DCT techniques. Firstly color and texture features are extracted, then applying Manhattan Distance, Euclidean Distance and Mean Square Error to measure the similarity of feature vectors in features database and feature vector for the query image.

A. HSV Vector Generation

The HSV provides the perception representation according with human visual feature. The HSV model defines a color space in terms of three constituent components: Hue, the color type range from 0 to 360 relative to the red primary at 0°, passing through the green primary at 120° and the blue primary at 240°, and then back to red at 360°. Saturation, the "vibrancy" of the color: Ranges from 0 to 100%. Value, the brightness of the color: it ranges from 0 to 100%. The HSV color space is used instead of the RGB color space due to two reasons: the lightness component is independent factor of images and the components of hue and saturation are so closely link with the pattern of human visual perception[21]. The conversion process of RGB to HSV color space is defined in Equations (4),(5) and (6).

$$H = cos^{-1}\frac{\frac{1}{2}[R-G]+[R-B]}{\sqrt{(R-G)^2-(G-B)(R-B)}} \quad (4)$$

$$S = 1-\left(\frac{3[min(R,G,B)]}{R+G+B}\right) \quad (5)$$

$$V = \left(\frac{R+G+B}{3}\right) \quad (6)$$

The algorithm for color feature vector generation is formulated in following steps:

Step1: Read the image.

Step2: Convert RGB color space image into HSV color space.

Step 3: Color quantization is carried out using color histogram by assigning eight levels for each to Hue, Saturation and Value to give a quantized HSV space with 8*8*8=512 histogram bins.

Step 4: Histogram is obtained by dividing the pixel which represents the color on the total number of pixels.

Step 5: Compute HSV histogram for all color intensities in the image.

Step 6: Store the value of bins of color histograms in three vectors, one for each HSV color space.

Step 7: Repeat step1 to step 6 on all images in the database.

Step 8: All these color histograms are combined after then in one vector with the values of DCT to search for similar images in database.

B. DCT Vector Generation

For the DCT transform, a query image is given and converted into a gray level image. The texture feature vector is gained from some DCT coefficients. It is computed directly from the DCT coefficients and the spatial localization using sub blocks. Each image is divided into ***N*N*** sized sub-blocks. The two dimensional DCT can be defined in terms of pixel values ***f(i, j)*** for ***i,j*** = 0,1,… ***N***-1 and the frequency-domain transform coefficients ***C(u,v)*** as explained in Equation (7)[22].

$$c(u,v) = \alpha(u)\alpha(v)\sum_{X=0}^{N-1}\sum_{y=0}^{N-1} f(x,y)\cos\left(\frac{\pi(2x+1)u}{2N}\right)\cos\left(\frac{\pi(2y+1)v}{2N}\right) \quad (7)$$

$$\alpha(u) = \begin{cases}\sqrt{\frac{1}{N}}, for\ u=0 \\ \sqrt{\frac{2}{N}}, for\ u\neq 0\end{cases}$$

Where,
u : indicates regular frequency spatially,
v : indicates perpendicular frequency spatially,
f(x, y) : the pixel value at (x, y),
C(u, v) : DCT coefficient at (u, v).

The algorithm for texture feature vector generation goes through the following steps:

Step 1: Read the image.

Step 2: Convert RGB into gray scale.

Step 3: Partition the image into 8x8 blocks.

Step4: Apply DCT on each block to acquire DC coefficients.

Step 5: Store the value of DC coefficients in one vector.

Step 6: Repeat step1 to step 5 on all images in the database.

Step 7: Combine the vector of DC coefficients with the vectors of color histograms in one vector.

C. Feature Similarity Measurement Process

For evaluation purpose, similarity measurement is conducted to compare query image with other images resided in images database.

If ***I*** is the database image and ***Q*** is the query image, then the algorithm of similarity measure is calculated as in the following steps:

Step 1: Compute color histogram vector vI and DCT vector dI of the database images then combine them into a single vector.

Step 2: Calculate the vectors vQ and dQ for the query image also.

Step 3: One measure of distance between two feature vectors will be used for the similarity measurement.

Step 4: From all, the matching images are the top 20 images which displayed as a result.

Overall Scheme of Implemented Approach is explained in Fig 1.

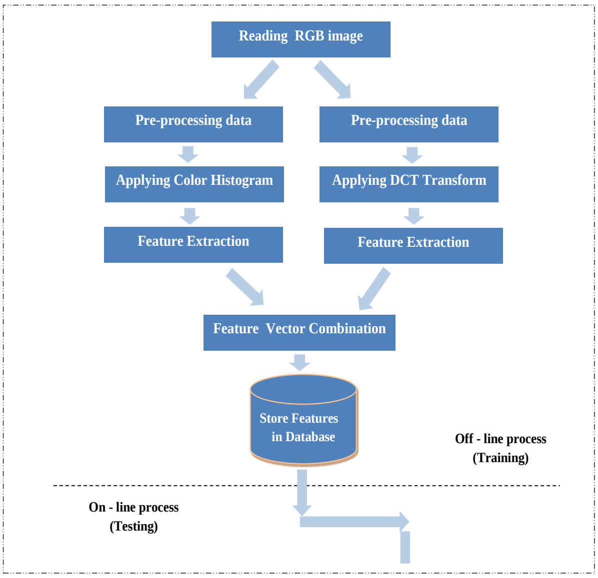

Fig 1: Architecture of The Proposed Approach

VI. RESULTS AND DISCUSSION

The performance efficiency of the prototype system and execution time are tested using some similarity measures.

A. *Evaluation Measures for CBIR System*

There are several ways to evaluate the performance of CBIR systems and measure their efficiency, the most famous are precision and recall.

Precision can be seen as a measure of exactness or quality. On the other hand, recall is a measure of completeness or quantity. Simply, high precision denotes that an algorithm returned substantially more relevant results than irrelevant ones, while high recall means that an algorithm returned most of the relevant results. Precision and recall are defined in Equations (8) and (9).

$$\text{Precision} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of images retrieved}} = \frac{A}{B} \quad (8)$$

$$\text{Recall} = \frac{\text{Number of relevant images retrieved}}{\text{Total number of relevant images in the dataset}} = \frac{A}{C} \quad (9)$$

Where A is the set of retrieved images matching the query, B is the set of returned images, and C is the set of images matching the query in the database[5].

B. *The proposed Approach Evaluation*

The proposed prototype system is tested and evaluated as follows. First, it is evaluated using several distance measures, then it is compared with previous studies. A Corel 1-k dataset is used for evaluation purpose, which is very widely used in CBIR systems. It contains 1000 color images and is divided into 10 categories, each category contains 100 images.

To find the similar images, the feature of query image is compared with feature of images database by Manhattan, Euclidean and Mean Squared Error methods which calculate the minimum distance. The prototype system retrieves the top 10 or 20 images similar to the query image depending on the user's interest. The retrieved results are a list of images arranged by their similarity distances to the query image. For each category, four images are selected randomly, and there average is calculated.

In order to test and evaluate the proposed prototype system, a graphical user interface described in Fig 2 is designed to allow the selection of the required similarity measurement unit as well as the number of images retrieved in the retrieval process.

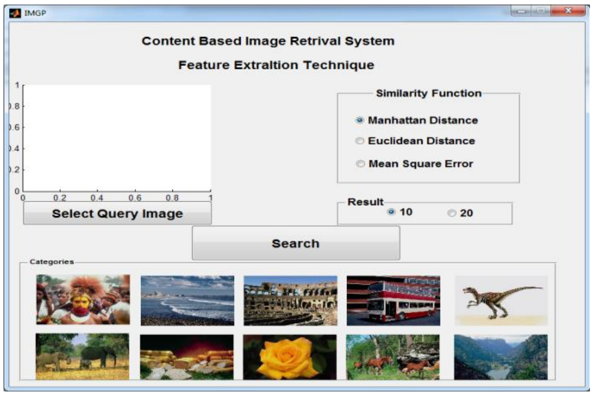

Fig 2: Main UI for CBIR prototype system

In Fig 3, a query image and its results appear. A random image was selected from Bus category and 20 images were retrieved as a result. All retrieved images belong to the same category as the query image .The test shows that, the system is effective in retrieving images similar to the query image. The results are good, even with different color of the Bus, because the system does not rely on the color feature only, thus the result of retrieval is improved by integrating the texture feature. Most Buses show the same size and shape as the bus query image.

Fig 3: Top-20 retrieval result for Bus image

Fig 4 shows top 20 retrieved Images for the same query image from Dinosaur category, for example. The system proved efficiency of retrieving all images similar of the query image.

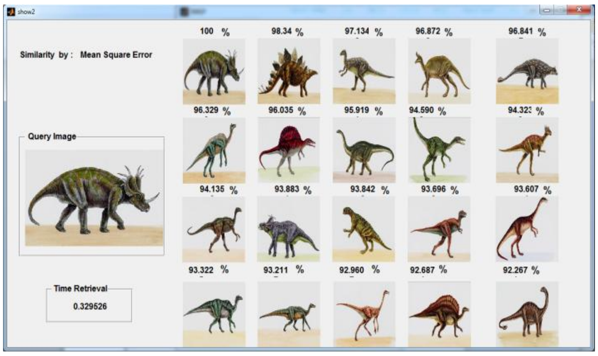

Fig 4: Top-20 retrieval result for Dinosaur image

The general average for precision and recall was calculated to retrieve the image using the three methods for measuring similarity. In terms of precision, MD similarity measure was the best, followed by the ED similarity measure and finally the MSE similarity measure with little difference. The average values are shown in Table I The recall values also shown in this table.

Table I : Average Precision and Recall using Three Similarity Measures

	Precision		Recall	
similarity measure	10 images	20 images	10 images	20 images
MD	0.8850	0.8180	0.0840	0.1640
ED	0.8595	0.7540	0.0863	0.1508
MSE	0.8445	0.7338	0.0750	0.1390

The precision and recall values of the retrieved results by three similarity measures are represented graphically in Fig 5 and Fig 6.

FIG 5: COMPARISON OF PRECISION OF 20 IMAGES

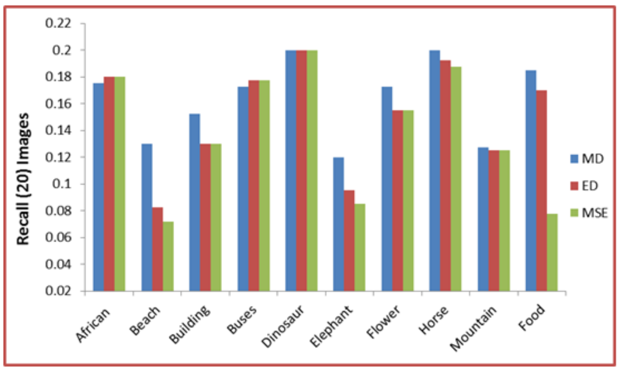

Fig 6: Comparison of recall of 20 images

C. Comparison of the proposed Approach with previous studies

The results of the proposed approach are compared with other previous studies which are selected for performance comparison as reported by[20]. For comparison, MD similarity measure is chosen since it produced better results than others in the proposed approach. The comparison results are shown in Table II, which clarify that the performance of the proposed approach was better than other previous studies in most categories, except for Bus category, while the accuracy was equal in Dinosaur category. Table III shows the comparison of the recall measure of proposed approach with other previous studies.

Table II : Average Precision of all Image Categories with Other Previous Studies

Category	M.E. Elalami[32]	J.Yue etl [4]	J. Yu etl [7]	S.Somnug etl [18]	A. Nazir etl [31]	Result of Approach
Africa	0.58	0.53	0.57	0.676	0.85	0.875
Beach	0.41	0.45	0.58	0.598	0.50	0.650
Building	0.42	0.46	0.43	0.58	0.75	0.763
Bus	0.71	0.84	0.93	0.94	1	0.863
Dinosaur	0.74	0.90	0.98	0.998	1	1
Elephant	0.65	0.72	0.666	0.58	0.55	0.600
Flower	0.83	0.74	0.83	0.886	0.95	0.863
Horse	0.69	0.72	0.68	0.938	0.90	1
Mountain	0.44	0.53	0.46	0.478	0.30	0.638
Food	0.44	0.46	0.53	0.492	0.55	0.925
Average	0.595	0.641	0.650	0.725	0.735	0.818

Table III : Average Recall of all Image Categories with Other Previous Studies

Category	M.E. Elalami[32]	J.Yue etl [4]	J. Yu etl [7]	S.Somnug etl [18]	A. Nazir etl [31]	Result of Approach
Africa	0.12	0.11	0.11	0.13	0.17	0.175
Beach	0.08	0.09	0.12	0.12	0.10	0.130
Building	0.08	0.09	0.08	0.12	0.15	0.153
Bus	0.14	0.17	0.19	0.19	0.20	0.173
Dinosaur	0.15	0.18	0.19	0.19	0.20	0.2
Elephant	0.13	0.15	0.12	0.13	0.11	0.120
Flower	0.17	0.15	0.16	0.18	0.19	0.173
Horse	0.14	0.14	0.13	0.19	0.18	0.2
Mountain	0.09	0.11	0.09	0.09	0.06	0.128
Food	0.09	0.09	0.10	0.10	0.11	0.185
Average	0.119	0.128	0.129	0.144	0.147	0.164

VII. CONCLUSION

This paper suggests a color images retrieval approach based on the image content. Color and texture features are extracted to represent the image content. Then, various distance metrics for the performance analysis are used. In order to extract color and texture features, the color histogram and DCT techniques are used respectively, then these features are integrated into a single vector representing the image in numerical values to compare it with the vector of the query image using MD, ED and MSE functions to measure the similarity. Performance of the proposed approach was evaluated using three similarity measures. MD similarity measure proved its effectiveness in the retrieval process, as well as in the response time compared to other similarity measures. The proposed approach was evaluated and compared with some previous studies. It has proved its effectiveness in retrieval process, and it has good performance in precision with rate (8.3%) compared with the best result of other studies. This means that using the proposed approach has improved the process of retrieving color images in means of accuracy and response time.

REFERENCES

[1] H. H. Wang, D. Mohamad, and N. A. Ismail, "Approaches, challenges and future direction of image retrieval," arXiv preprint arXiv:1006.4568, 2010.

[2] S. Lata and P. P. Singh, "A Review on Content Based Image Retrieval System," International Journal of Advanced Research in Computer Science and Software Engineering (IJARCSSE), ISSN, vol. 2277, 2014.

[3] R. S. Patil and A. J. Agrawal, "Content-based image retrieval systems: a survey," Advances in Computational Sciences and Technology, vol. 10, pp. 2773-2788, 2017.

[4] W. Zhou, H. Li, and Q. Tian, "Recent advance in content-based image retrieval: A literature survey," arXiv preprint arXiv:1706.06064, 2017.

[5] A. J. Afifi and W. M. Ashour, "Image retrieval based on content using color feature," International Scholarly Research Notices, vol. 2012, 2012.

[6] A. S. GOMASHE and R. KEOLE, "A Novel Approach of Color Histogram Based Image Search/Retrieval," International Journal of Computer Science and Mobile Computing, pp. 57-65, 2015.

[7] M. Gupta and A. K. Garg, "Analysis of image compression algorithm using DCT," International Journal of Engineering Research and Applications (IJERA), vol. 2, pp. 515-521, 2012.

[8] D. T. i Hasta, "Fast Discrete Cosine Transform Algorithm Analysis on IJG JPEG Compression Software," Faculty of Industrial Technology, Gunadarma University, Gunadarma University, 2012.

[9] G. Sorwar and A. Abraham, "DCT based texture classification using soft computing approach," arXiv preprint cs/0405013, 2004.

[10] T. Tsai, Y.-P. Huang, and T.-W. Chiang, "Image retrieval based on dominant texture features," in 2006 IEEE International Symposium on Industrial Electronics, 2006, pp. 441-446.

[11] F. Malik and B. Baharudin, "Analysis of distance metrics in content-based image retrieval using statistical quantized histogram texture features in the DCT domain," Journal of king saud university-computer and information sciences, vol. 25, pp. 207-218, 2013.

[12] Y. Mistry, D. Ingole, and M. Ingole, "Content based image retrieval using hybrid features and various distance metric," Journal of Electrical Systems and Information Technology, 2017.

[13] K. Ponnmoli and D. S. Selvamuthukumaran, "Analysis of Face Recognition using Manhattan Distance Algorithm with Image Segmentation," International Journal of Computer Science and Mobile Computing, vol. 3, pp. 18-27, 2014.

[14] F. Memon, M. A. Unar, and S. Memon, "Image quality assessment for performance evaluation of focus measure operators," arXiv preprint arXiv:1604.00546, 2016.

[15] M. H. Abed and D. S. J. Al-Farttoosi, "Content based Image Retrieval based on Histogram," International Journal of Computer Applications, vol. 110, 2015.

[16] P. Kar and L. Kumari, "Feature Based Image retrieval based on Color," International Research Journal of Engineering and Technology vol. 05, 2018.

[17] P. Hemalath, "Image Retrieval by content using DCT and RGB Projection," International Journal of Computer Science & Communication Networks, vol. 3, p. 134, 2013.

[18] C. Wang, X. Zhang, R. Shan, and X. Zhou, "Grading image retrieval based on DCT and DWT compressed domains using low-level features," Journal of Communications, vol. 10, pp. 64-73, 2015.

[19] L. V. Sree and K. Chaitanya, "Color Image Indexing by Exploiting the Simplicity of the EDBTC Method," International Journal of Research, vol. 04, 2017.

[20] A. Nazir, R. Ashraf, T. Hamdani, and N. Ali, "Content based image retrieval system by using HSV color histogram, discrete wavelet transform and edge histogram descriptor," in 2018 International Conference on Computing, Mathematics and Engineering Technologies (iCoMET), 2018, pp. 1-6.

[21] C.-H. Su, M. H. A. Wahab, and T.-M. Hsieh, "Image Retrieval based on color and texture features," in 2012 9th International Conference on Fuzzy Systems and Knowledge Discovery, 2012, pp. 1816-1819.

[22] P. H. Chandankhede, "Soft Computing Based Texture Classification with MATLAB Tool," International Journal of Soft Computing and Engineering, vol. 2, 2012.