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A NEW CONTENT BASED IMAGE RETRIEVAL SYSTEM USING GMM AND RELEVANCE FEEDBACK

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ABSTRACT

Content-Based Image Retrieval (CBIR) is also known as Query By Image Content (QBIC) is the application of computer vision techniques and it gives solution to the image retrieval problem such as searching digital images in large databases. The need to have a versatile and general purpose Content Based Image Retrieval (CBIR) system for a very large image database has attracted focus of many researchers of information-technology-giants and leading academic institutions for development of CBIR techniques. Due to the development of network and multimedia technologies, users are not fulfilled by the traditional information retrieval techniques. So nowadays the Content Based Image Retrieval (CBIR) are becoming a source of exact and fast retrieval. Texture and color are the important features of Content Based Image Retrieval Systems. In the proposed method, images can be retrieved using color-based, texture-based and color and texture-based. Algorithms such as auto color correlogram and correlation for extracting color based images, Gaussian mixture models for extracting texture based images. In this study, Query point movement is used as a relevance feedback technique for Content Based Image Retrieval systems. Thus the proposed method achieves better performance and accuracy in retrieving images.

Keywords: Image Retrieval, Texture, Auto Color Correlogram (ACC), Gaussian Mixture Models, Query Point Movement

1. INTRODUCTION

Content-based image retrieval technique uses visual contents to search images from large scale image databases based on users' interests. It becomes an active and fast advancing research area. Image content may include both visual and semantic content. Content-Based Image Retrieval (CBIR) is a technique for retrieving images on the basis of automatically-derived features such as color, texture and shape (Singh *et al*., 2012). These techniques includes several areas such as image segmentation, image feature extraction, representation, mapping of features to semantics, storage and indexing, image similarity-distance measurement and retrieval which makes CBIR system development as a challenging task (Chauhan and Goyani, 2013). Several companies are maintaining large image databases, where the requirement is to have a technique that can search and retrieve images in a manner that is both time efficient and accurate (Xiaoling, 2009).

Visual content can be very general or domain specific. General visual content include color, texture, shape, spatial relationship. Domain specific visual content, like human faces, is application dependent and may involve domain knowledge. Semantic content is obtained either by textual annotation or by complex inference procedures based on visual content. A visual content descriptor can be either global or local. A global descriptor uses the visual features of the whole image, whereas a local descriptor uses the visual features of regions or objects to describe the image content. To obtain the local visual descriptors, an image is often divided into parts first. The simplest way of dividing an image is to use a partition, which cuts the image into tiles

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of equal size and shape. A simple partition does not generate perceptually meaningful regions but is a way of representing the global features of the image at a finer resolution. A better method is to divide the image into homogenous regions according to some criterion using region segmentation algorithms that have been extensively investigated in computer vision. A more complex way of dividing an image, is to undertake a complete object segmentation to obtain semantically meaningful objects (like ball, car, horse). Currently, automatic object segmentation for broad domains of general images is unlikely to succeed.

Color is the most extensively used visual content for image retrieval (Khutwad and Vaidya, 2013) Its three-dimensional values make its discrimination potentiality superior to the single dimensional gray values of images. Before selecting an appropriate color description, color space must be determined first. There are many color spaces used to represent the image (RGB, HSV, CIE) and many approaches used for representation, such as histograms, binary sets (Wei *et al*., 2009) and correlogram. The proposed method uses auto color correlogram for color representation.

Texture refers to the visual patterns that have properties of homogeneity. It does not result from the presence of only a single color or intensity. It is an innate property of virtually all surfaces of real-world objects such as clouds and fabrics. Texture contains information about the structural arrangement of surfaces and their relationship to the surrounding environment. Popular texture representations include co occurrence matrix, Tamura texture and Wavelet texture. The proposed method uses Gaussian mixture models for texture representation.

Relevance Feedback (RF) is the process of automatically adjusting an existing query using the information feedback by the user about the relevance of previously retrieved objects such that the adjusted query. The key issue in relevance feedback is how to effectively utilize the feedback information to improve the retrieval performance (Xin and Jin, 2004). After obtaining the retrieval results, user provide the feedback as to whether the results are relevant or non relevant. If the results are non-relevant the feedback loop is repeated many times until the user is satisfied. In the proposed method Relevance feedback technique can be done using decision trees.

Query-by-example is a specification mechanism in which an existing image is used as a query (Niblack *et al*., 1993). It implicitly facilitates retrieving images based on their low-level features and is not appropriate or feasible in certain domains as well as for certain types of users. A natural extension to querying based on low-level image features is to query images at the domain object level. For example, “retrieve images that contain a flower” is a query at the domain object level. A domain object is a semantic abstraction and at the physical level, it may correspond to multiple geometric regions in the image.

The paper can be organized as follows: Section II describes the related works involved in content based image retrieval, Section III describes the methodology used to retrieve the images, Section IV describes Experimental results obtained by using proposed methodology.

1.1. Related Works

Jain and Singh (2011) provided an overview of the functionality of content based image retrieval systems by combining advantages of HC and divide and conquer K-Means strategy. He proposed HDK method to use both advantages of HC and Divide and conquer K-Means by introducing equivalency and compatible relation concepts. Penatti *et al*. (2012) presented a comparative study of color and texture descriptors by considering the Web as the environment of use. The diversity and large-scale aspects of the Web considering a large number of descriptors (24 color and 28 texture descriptors, including both traditional and recently proposed ones) were also taken into account in his research. He made the evaluation based on two levels: A theoretical analysis in terms of algorithms complexities and an experimental comparison considering efficiency and effectiveness aspects.

Singha and Hemachandran (2012) presented the content based image retrieval using features like texture and color, called Wavelet Based Color Histogram Image Retrieval (WBCHIR). The texture and color features are extracted through wavelet transformation and color histogram and the combination of these features is robust to scaling and translation of objects in an image. He also demonstrated a promising and faster retrieval method on a WANG image database containing 1000 general-purpose color images.

Gudivada (2010) discussed an approach to improve retrieval effectiveness via relevance feedback in text retrieval systems. He also showed how these relevance feedback techniques have been adopted to CBIR context and their effect on retrieval effectiveness. The need for test collections in advancing CBIR research is also discussed in his work.

Pinjarkar *et al*. (2012) discussed various methodologies used in the research area of Content Based Image Retrieval techniques using Relevance Feedback. To improve the retrieval performance of the

CBIR the Relevance Feedback technique can be incorporated in CBIR system to obtain the higher values of the standard evaluation parameters used for evaluation of the CBIR system which may lead to better results of retrieval performance. He also discussed various relevance feedback techniques for Content Based Image Retrieval systems, the various parameters used for experimental evaluation of the systems and the analysis of these techniques on the basis of their results.

Zhu *et al*. (2006) proposed a human detection algorithm using Histograms of Oriented Gradients (HOG) which are similar with the features used in the SIFT descriptor. HOG features are calculated by taking orientation histograms of edge intensity in a local region. They are designed by imitating the visual information processing in the brain and have robustness for local changes of appearances and position. Zhu *et al*. (2006) extracted the HOG features from all locations of a dense grid on a image region and the combined features are classified by using linear SVM. They showed that the grids of HOG descriptors significantly outer-performed existing feature sets for human detection. Kobayashi *et al*. (2008) applied Principal Components Analysis (PCA) to reduce the dimensionality of the feature vectors and tested them in an image retrieval application.

Patil and Kokare (2011) provides an overview of the technical achievements in the research area of Relevance Feedback (RF) in Content-Based Image Retrieval (CBIR). It also covers the current state of art of the research in relevance feedback in CBIR, various relevance feedback techniques and issues in relevance feedback.

Bulo *et al*. (2011) proposed a novel approach to content-based image retrieval with relevance feedback, which is based on the random walker algorithm introduced in the context of interactive image segmentation. The idea is to treat the relevant and non-relevant images labeled by the user at every feedback round as "seed" nodes for the random walker problem. The ranking score for each unlabeled image is computed as the probability that a random walker starting from that image will reach a relevant seed before encountering a non-relevant one.

2. MATERIALS AND METHODS

The visual contents of the images in the database are extracted and described by multi-dimensional feature vectors. The feature vectors of the images in the database form a feature database. To retrieve images, users provide the retrieval system with example images or sketched figures. The system then changes these examples into its internal representation of feature vectors. The similarities/distances between the feature vectors of the query example or sketch and those of the images in the database are then calculated and retrieval is performed with the aid of an indexing scheme.

The proposed method comprises three types of techniques to retrieve the content based images which is illustrated in **Fig. 2** and the overall process is shown in **Fig. 1**. They are as follows:

- Color- based image retrieval
- Texture- based image retrieval
- Color and texture based image retrieval

2.1. Color-Based Image Retrieval

Color is the important perceptual features. Color becomes one of the features of commercial CBIR systems. A color correlogram (henceforth correlogram) states how the spatial correlation of pairs of colors changes with distance. Auto color correlogram is an extension of the correlogram technique for color indexing. The proposed method uses auto color correlogram for color based image retrieval.

2.1.1. Auto Color Correlation Algorithm

An auto color correlation defines how to compute the mean color of all pixels of color C_j at a distance k-th from a pixel of color C_i in the image. Premchaiswadi and Tungkasthan (2011) formally, the ACC of image {I(x,y),x = 1,2,…,M,y = 1,2,…,N } is defined as Equation (1):

$$ACC(i,j,k) = MC_j Y^{(k)}_{C_iC_j}(I) = \{r_{mcj}\gamma^{(k)}_{C_iC_j}(I), g_{mcj}\gamma^{(k)}_{C_iC_j}(I), b_{mcj}\gamma^{(k)}_{C_iC_j}(I) \mid c_i{}^1c_j \quad (1)$$

where, the original image I(x,y) is quantized to m colors $C_1,C_2,\ldots,C_m$ and the distance between two pixels k∈[min{M,N}] is fixed a priori. Consider MC_j be the RGB value of color m in an image I. The mean colors are defined as follows Equation (2 to 4):

$$r_{mcj}\gamma^{(k)}_{C_iC_j}(I) = \frac{\prod_n^{nc_i,rc_j(k)}(I)}{\prod_n^{nc_i,c_j(k)}(I)} \mid c_i{}^1c_j \quad (2)$$

$$g_{mcj}\gamma^{(k)}_{C_iC_j}(I) = \frac{\prod_n^{nc_i,gc_j(k)}(I)}{\prod_n^{nc_i,c_j(k)}(I)} \mid c_i{}^1c_j \quad (3)$$

$$b_{mcj}\gamma^{(k)}_{C_iC_j}(I) = \frac{\prod^{(k)}_{c_i,bc_j}(I)}{\prod^{(k)}_{c_i,c_j}(I)} \Big| c_i \neq c_j \quad (4)$$

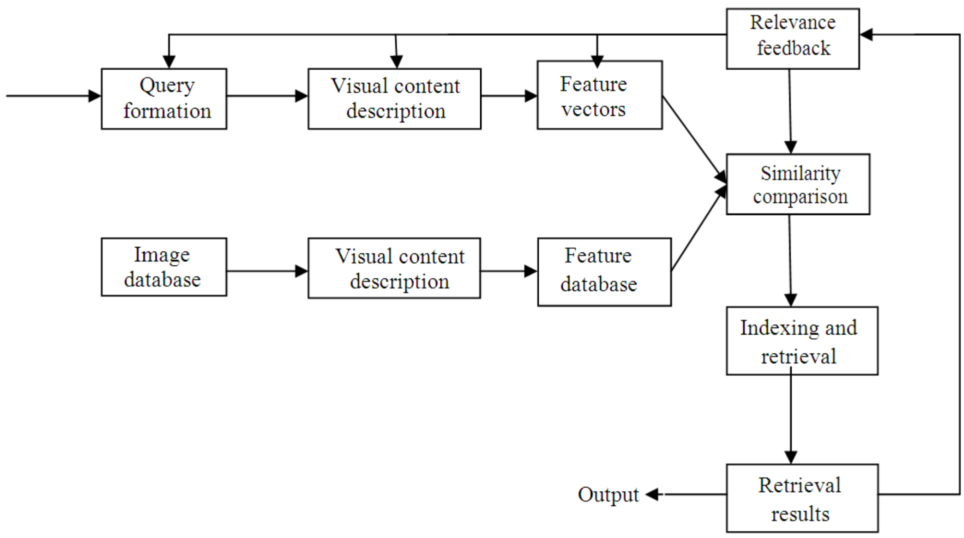

Fig. 1. Process involved in content based image retrieval

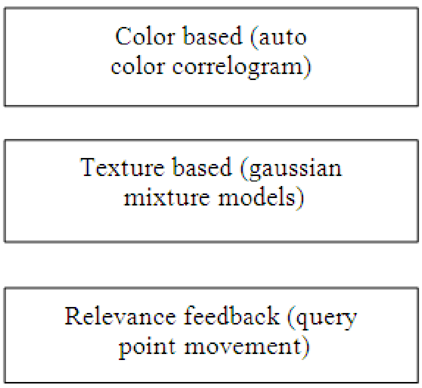

Fig. 2. Algorithms used in the proposed method

where, denominator $\prod_{c_i, xc_j}^{(k)}$ is the total of pixels values of color C_j at distance k from any pixel of color C_i when x is RGB color space and denoted $C_j \neq 0$. N represents the number of accounting color C_j from color C_i at distance k is computed as follows Equation (5):

$$N = \prod_{c_i c_j}^{(k)} (I) \quad \begin{cases} P(x_1, y_1) \in C_i \ / \ P(x_2, y_2) \in C_j \\ k = \min\{|x_1 - x_2|, |y_1 - y_2|\} \end{cases} \tag{5}$$

By reducing the size of color correlogram from $O(m^2d)$ to O(3md), ACC can be able to find the local spatial correlation between color. To decrease the storage space required and increase the speed of retrieval, the size of ACC can be reduced from O(3md) to O(m). By using this algorithm, dominant RGB peaks values in any color bins are captured. The dominant elements are compared inorder to reduce the feature storage amount and speed of retrieval while processing similarity calculation of the two images:

```
For every K distance {
For every X position
   For every Y position {
        Ci ← current pixel
        While (Cj ←
               Get neighbors pixel of Ci ) at distance K)
        {
         For every color Cm {
         If (Cm = Ci and Ci ≠ Cj){
                countColor++
                colorR[Cm ] = colorR[Cm ] + colorRCj
                colorG[Cm ] = colorG[Cm]+ colorGCj
                colorB[Cm] = colorB[Cm] + colorBCj
                               }
                          }
         }
         }
meanColorR = sum ( colorR[Cm ])/countColor
meanColorG = sum ( colorG[Cm ])/countColor
meanColorB = sum ( colorB[Cm ])/countColor
}
```

The similarity of binary codes for auto color correlation, can be measured using intersection technique. It measures the similarity of binary codes for the same color between the query and model images. Consider $Bc_m(I) = b_1^r, b_2^r, ..., b_m^r; b_1^g, b_2^g, ..., b_m^g; b_1^b; b_2^b, ..., b_m^b$ represents the binary code of auto color correlation colors to color Cm in RGB space of query image I, then the intersection result of query image and model image concerning color Cm should be calculated.

The proposed method first computes the mean pixel value of the whole small block (4×4) and it compares each pixel to the block mean. If the pixel value is greater than or equal to the block mean, respective pixel position of the bitmap will have the value 1, otherwise it will be assigned as 0. When the RGB values in a color bin of ACC exceed a given threshold, then the bin is classified as effective, else it is classified as non-effective. Binary "1" is assigned to effective bin and, binary "0" is assigned to non effective bin. Thus by using feature vector of ACC in RGB color space, the accuracy of retrieval process can be improved.

2.2. Texture-Based Image Retrieval

Texture is a visual prompt which has been intensively used in pattern recognition. Two issues should be addressed while using texture for image retrieval:

- To capture human perception of texture and
- To find a distance function that measures the similarity between texture patterns

The proposed method uses gaussian mixture models to retrieve texture images.

2.2.1. Gaussian Mixture Models

Gaussian mixture models is one of the density model which includes a number of component Gaussian functions. These functions are combined with different weights to form a multi-modal density. Gaussian mixture models are a semi-parametric which can be used instead of non-parametric histograms (which can also be used to approximate densities). It has high flexibility and precision in modeling the underlying distribution of sub-band coefficients.

Consider N texture classes labeled by n ∈N ≅{1,….N} related to different entities. In order to classify a pixel, neighbourhood of that pixel must be considered. Then S×S sub-images blocks features can be computed assign classes to these blocks (Permuter *et al*., 2003). The set of blocks is represented by B. The neighbourhood of a block b is called patch P(b). It should be defined as the set of blocks in a larger T×T sub-image with b at its centre. D_b is denoted as the data associated to that block and $V_b \in N$ be the classification of b. The classification can be done based on the following rule Equation (6):

$$v_b = \arg\max_{n \hat{I} N'} \prod_{b' \hat{I} P(b)} Pr(Db' \mid vb' = n) \tag{6}$$

Thus, all the blocks in P(b) which has class n maximizes the probability of the data in P(b). It reduces computation time to classify the texture. The data D_b associated with each block is denoted by the vector of features $\vec{x}$. For each and every texture class, a probability distribution that represents the feature statistics of a block of that class must be selected. Thus the probability that obtained $\vec{x}$ will be a convex combination of M Gaussian densities Equation (7):

$$P(\vec{x} \left| \{p_i, \vec{\mu} \textstyle\sum_i \}\right.) = \sum_{i=1}^{M} p_i\, b(\vec{x}, \vec{\mu}_i \textstyle\sum_i) \tag{7}$$

where, is $b(\vec{x}, \overline{\mu_i \sum_i})$ Gaussian of mean $\overline{\mu_i}$ and covariance $\sum$ The parameters for a given class are thus $\{p_i, \overline{\mu_1} \sum_i | i \in M\}$.

A GMM is the natural model which can be if a texture class contains a number of distinct subclasses. Thus by using Gaussian mixture model to retrieve the texture properties of the image gives desired accuracy.

2.3. Color and Texture-Based Image Retrieval

By combining both the proposed algorithms such as Auto color correlation and Gaussian mixture models, color and texture properties can be retrieved.

2.4. Relevance Feedback

Every user's need will be different and time varying. A typical scenario for relevance feedback in content-based image retrieval is as follows (Patil and Kokare, 2011):

Step 1: Machine provides initial retrieval results
Step 2: User provides judgment on the currently displayed images based on the degree whether they are relevant or irrelevant to her/his request
Step 3: Machine learns the judgment of the user and again search for the images according to user query. Go to step 2

The proposed method uses Query point movement for relevance feedback.

3.4.1. Query Point Movement

Query is indicated by a single point in a feature space and this point is moved towards the direction where relevant points are located by refinement process. Rocchio's formula is the mostly used technique to iteratively improve this estimation (Rocchio, 1971) Equation (8):

$$q_{n+1} = aq_n + \frac{\beta}{N+(n)}\sum_{j=1}^{Jerl} X_j - \frac{\gamma}{N-(n)}\sum_{j=1}^{jnon\_rel} Y_j \qquad (8)$$

where, q_n is the query point for nth round of the search cycle. parameters α, β and γ are the suitable constants denoted as the weight parameters; J rel is the number of relevant images in Xj and Jnon_rel is the total number of non-relevant images in Yj. The parameters β and γ can be adjusted to be more biased towards one sample group depending on the nature of the data samples. If variable γ is set to zero, then the negative sample may totally ignored and by setting variable α to zero the history of the query point can be ignored (Patil and Kokare, 2011).

3. RESULTS AND DISCUSSION

The main goal of this experiment is to find the relevant images for the given input query with few numbers of iterations. To compare the performance of this approach it is compared with existing work proposed by Beecks *et al*. (2011). The accuracy of the image can be calculated by the following formula:

$$\text{Accuacy} = \frac{N - X}{N} * 100$$

where, N is number of relevant images in the database which are known to the user and X is the number of irrelevant images in the database which are known to the user.

3.1. Color Based Image Retrieval

The user will give input query image. The image is searched automatically in the database based on the color and searched images will be displayed. The system gets relevance feedback from the user and do the same process recursively until all relevant images are obtained.

The input query is shown in the **Fig. 3**. For example consider elephant as an input query given by the user.

Iteration 1 (Before Relevance Feedback)

Figure 4 reveals the output images based on the user's input query. The images will be searched based on the color of the given input. In the given example the last image is an irrelevant image. Therefore according to the user's feedback, the system search the images again in the database. The accuracy of the output images in the first iteration is 83%.

Iteration 2 (After Relevance Feedback):

Figure 5 shows the output images after relevance feedback. since all the relevant images are obtained in the second iteration, the system stops searching images in the database. The accuracy of images obtained in the second iteration is 100%. If all the output images are not relevant, the database will proceed upto nth iteration until all relevant images are obtained and it stops when it gets 100% accuracy. Thus the proposed approach obtains maximum accuracy in retrieving color based images.

3.2. Texture Based Image Retrieval

The system search images based on the texture given by user's input query image. The query image is searched in the database based on the texture and system displays the output images. Based on the relevance feedback, the system search images in the database and displays the images. The input query is shown in the **Fig. 3**.

Iteration 1 (Before Relevance Feedback)

Figure 6 illustrates the output images based on the user's input query. Based on the texture of the given input, the images will be searched in the database. In the given example, the last three images is an irrelevant image. The system search the images again in the database according to the user's feedback.The accuracy of the output images obtained in the first iteration is 50%.

Iteration 2 (After Relevance Feedback)

Figure 7 represents the output images based on texture after relevance feedback. The accuracy of images obtained in the second iteration is 83%. Still few irrelevant images are in the output image, it will be proceeded upto nth iteration until maximum accuracy is obtained.

Iteration 3 (After Relevance Feedback)

Figure 8 shows the images after third iteration. The accuracy obtained in the third iteration is 100%. Since maximum accuracy is reached in the third iteration it stops searching images in the database.

Fig. 3. Input query

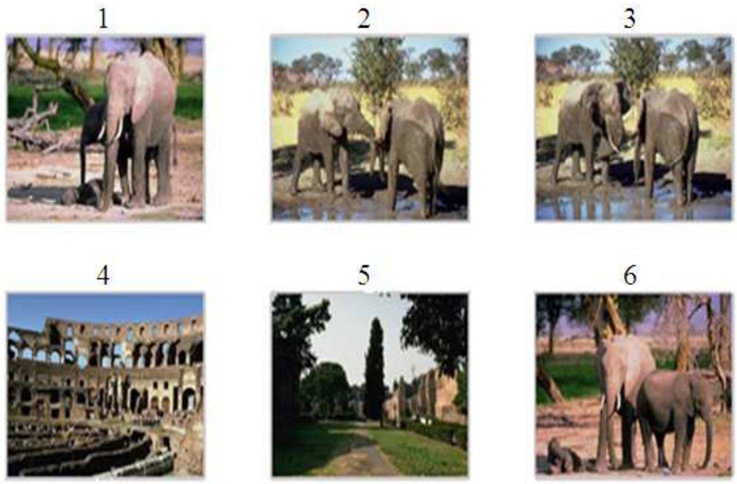

Fig. 4. Output image before relevance feedback using color-based image retrieval

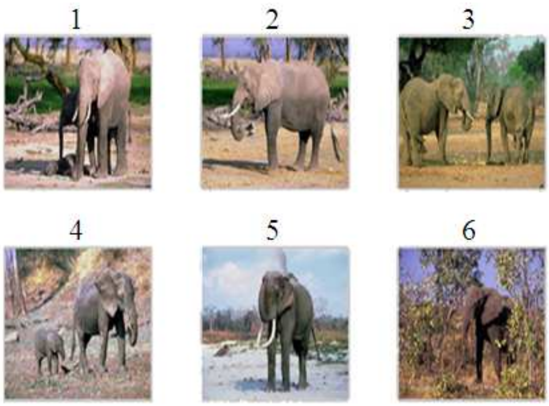

Fig. 5. Output image after relevance feedback using color-based image retrieval

Fig. 6. Output image before relevance feedback using texture-based image retrieval

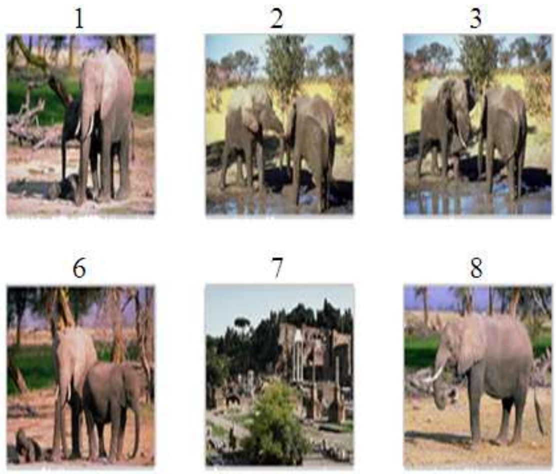

Fig. 7. Output image 1 after relevance feedback using texture-based image retrieval

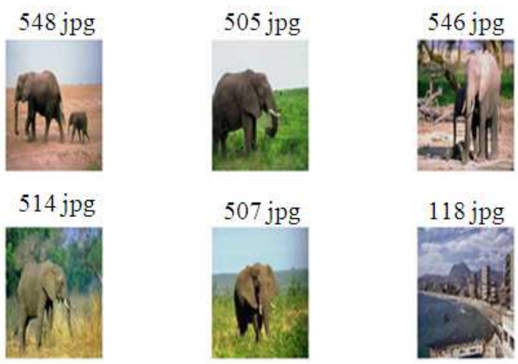

Fig. 8. Output image 2 after relevance feedback using texture-based image retrieval

3.3. Color and Texture Based Image Retrieval

Based on the user's input query, the image will be searched in the database. Here images are searched by both color and texture and the output is shown to the user. The user verifies whether the images are relevant and sends feedback to the system. The system process according to the user's feedback and displays the images. The same **Fig. 3** is used as an input query to find the images based on color and texture.

Iteration 1 (Before Relevance Feedback)

Figure 9 reveals the output images based on the user's input query. The system searches image based on color and texture in the image database. There is an irrelevant image in the output. Hence the system performs the image search again as per user's feedback. The accuracy of the output images obtained in the first iteration is 67%.

Iteration 2 (After Relevance Feedback)

Figure 10 shows the images obtained in the second iteration based on both the color and texture. It achieves maximum accuracy 100% in the second iteration. Thus the proposed method performs well in retrieving the images with maximum accuracy.

3.4. Performance Evaluation

The dataset consists of six different images. The corresponding accuracy of the query images to display these images before and after relevance feedback has been observed for color-based, Texture-based and color and texture-based image retrieval. The accuracy before and after relevance feedback for the color based image retrieval is shown in the **Table 1**.

Fig. 9. Output image before relevance feedback using both color and based image texture retrieval

Table 1. Accuracy comparison of color based image retrieval before and after relevance feedback

Query image	Accuracy before RF	Accuracy after RF	No. of iterations
Beaches	50	100	3
Building	67	100	3
Dinosaur	50	100	4
Elephant	83	100	2
Trees	83	100	3
Tiger	33	100	4
Average	61	100	3

Table 2. Accuracy comparison of texture based image retrieval before and after relevance feedback

Query image	Accuracy before RF	Accuracy after RF	No. of iterations
Beaches	67	100	3
Building	67	100	3
Dinosaur	83	100	2
Elephant	50	100	3
Trees	67	100	4
Tiger	50	100	6
Average	64	100	4

Table 3. Accuracy comparison of color & texture based image retrieval before and after relevance feedback

Query image	Accuracy before RF	Accuracy after RF	No. of iterations
Beaches	50	100	4
Building	67	100	5
Dinosaur	83	100	3
Elephant	67	100	2
Trees	67	100	4
Tiger	33	100	5
Average	61	100	4

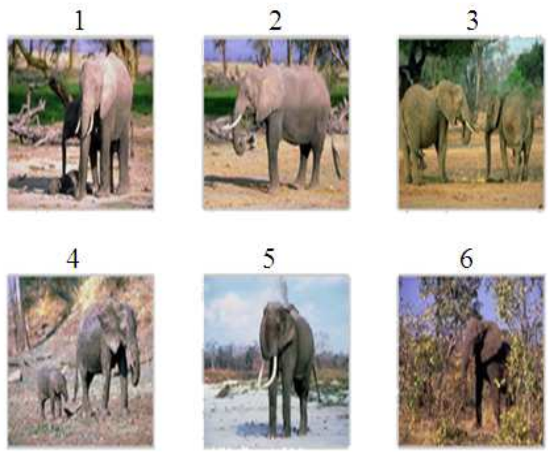

Fig. 10. Output image after relevance feedback using color and texture-based image retrieval

Table 1 illustrates that the average number of iteration for the six datasets is 3 and the maximum accuracy after relevance feedback is 100%.

The accuracy before and after relevance feedback for the texture based image retrieval is shown in the **Table 2**. It is clear that average accuracy before relevance feedback for the texture is 64%. The total no. of iterations is 4 and the maximum accuracy obtained is 100%.

Table 3 represents the accuracy obtained for color and Texture based image retrieval before and after relevance feedback. The average no. of iterations is 4 and the maximum accuracy obtained is 100%.

Figure 11 represents the Accuracy comparison of the Color based image retrieval before and after relevance feedback. It is clear from the figure that after relevance feedback, the maximum accuracy is obtained 2-4 iterations. Thus the proposed approach obtains maximum accuracy with relevance feedback in color based image retrieval.

Figure 12 indicates the Accuracy comparison of the Texture based image retrieval before and after relevance feedback. The maximum accuracy (100%) is obtained within 2-6 iterations after relevance feedback. Thus the proposed approach obtains maximum accuracy with relevance feedback for texture based image retrieval.

The Accuracy comparison of the Color and Texture based image retrieval before and after relevance feedback is revealed in **Fig. 13**. Within 2-5 iterations The maximum accuracy (100%) is obtained after relevance feedback. Thus the maximum accuracy is obtained with relevance feedback for Color and texture based image retrieval.

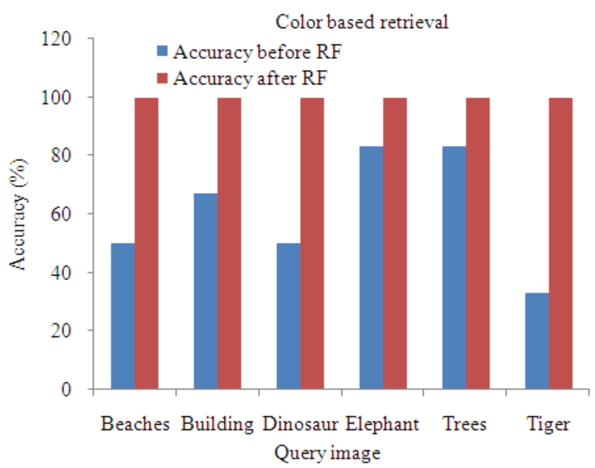

Fig. 11. Accuracy comparison of the color based image retrieval before and after relevance feedback

The experimental results proved that the proposed method achieves maximum accuracy with the help of relevance feedback in retrieving all the relevant images according to the query image given by the user. Hence proposed method gives better performance in retrieving all the relevant images in the database.

The **Table 4** gives the average result of existing technique named GQFD based image retrieval with our proposed technique GMM with RF for Corel Wang dataset. From the obtained result our method out performance from the GQFD result in the means of average accuracy of retrieval.

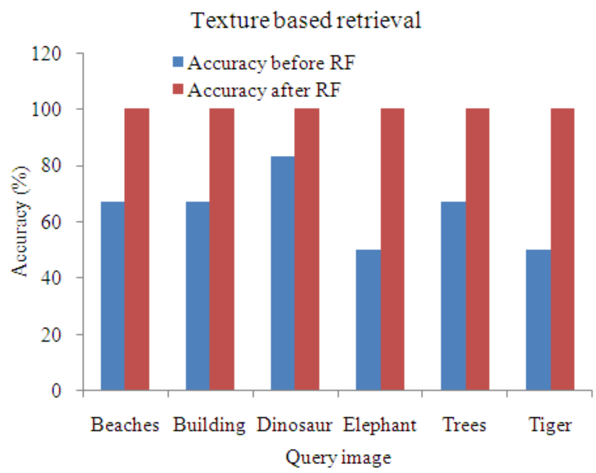

Fig. 12. Accuracy comparison of the texture based image retrieval before and after relevance feedback

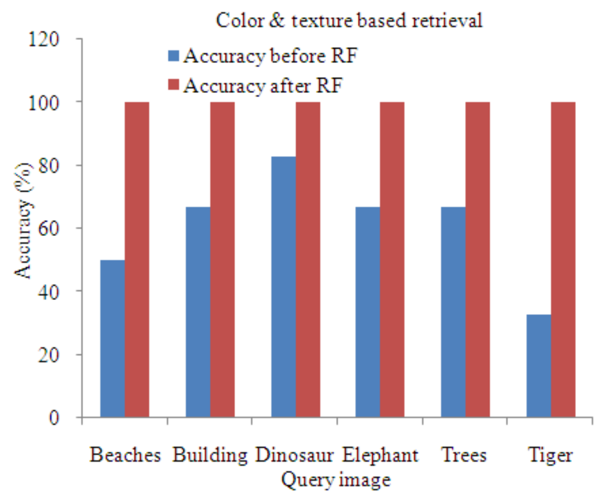

Fig. 13. Accuracy comparison of the color and texture based image retrieval before and after relevance feedback

Table 4. Average accuracy comparison between existing and proposed approach

Dataset	Technique	Average accuracy (%)
Corel wang	GQFD	45.7
	Proposed GMM-RF	61.1

4. CONCLUSION

Many companies facing problems in displaying relevant images from a bulk database. CBIR provides solution to these problems. The proposed method uses three approaches to retrieve the relevant images from the database. Images can be retrieved based on Color, Texture, both Color and texture respectively. The proposed method uses algorithms such as auto color correlogram to retrieve color based images, Gaussian mixture models to retrieve texture based images and Query point movement for relevance feedback. The experimental results conforms that the proposed method gives maximum accuracy when compared to existing work. This method lacks when the structure of object is similar between each other. As a future work, system can be redesigned to accept semantic in addition to content-based queries. To obtain integrated system texture features must be derived from other algorithms.

5. REFERENCES

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