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Multimodal Attributes to Perform CBIR for Multimedia and Medical Image Processing

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Abstract: In this Research, a novel method of combining the two techniques is proposed for query by example in CBIR. Query expansion is used to construct multipoint queries by clustering the relevant images. Query point movement is used to improve the representation of the multiple point queries by applying the Rocchio's technique on the relevant and the irrelevant images. Our contribution is a cluster-based relevance feedback technique, which uses the query point movement technique and the irrelevant examples to enhance the efficiency of query expansion. We made use of 3D Histogram Technique along with the corner detection with ORB. The descriptors make use of the region based slicing of the images to detect the accurate features from the images. The results shows that the accuracy is more compared to the other research papers and also the precision has been increased. For colour feature extraction, the conventional color histogram, euclidean distance method and the colour correlation method are also implemented and compared. For texture feature extraction, the gray level co-occurrence matrix is implemented. The aim of this paper is to clarify its potential usefulness to users in higher education and elsewhere.

Keywords: Inference mechanisms, multimedia databases, Content based image retrieval, Visual descriptor. ontology

I. INTRODUCTION

Content Based Image Retrieval (CBIR) is any technology that in principle helps to organize digital image archives by their visual content. By this definition, anything ranging from an image similarity function to a robust image annotation engine falls under the purview of CBIR The most common form of CBIR is an image search based on visual. The increasing amount of digitally produced images requires new methods to archive and access this data. Conventional databases allow for textual searches on Meta data only. Content Based Image Retrieval (CBIR) is a technique, which uses visual contents, normally called as features, to search images from large-scale image databases according to users' requests in the form of a query image [1], [2]. Colour, Shape and texture are important cue in extracting information from images; these histograms are widely used in content-based image retrieval [3]. Colour and texture contain important information but, for instance, two images with similar colour histograms can represent very different things. Therefore, the use of shape-describing features is essential in an efficient content-based image retrieval system. Although shape description has been intensively researched, there exists no direct answer as to which kind of shape features should be incorporated into such a system [4]. Most traditional and common methods of image retrieval utilize some method of adding metadata such as captioning, keywords or descriptions to the images so that retrieval can be performed over the annotation words. A query can be understood as the intentikon of a user to retrieve a certain kind of images, and it is usually materialized as one or more sample pictures. The goal of a CBIR system is to retrieve a set of images that is best suited to the user's intention. Obviously, the potential results of such a system will strongly depend not only on the particular features of the representation space but also on the implicit or explicit distance functions used to measure similarity between pictures [5], [6], [7].

This way of assessing similarity comes along with the implicit assumption that image resemblance is related to a distance defined over a particular feature space. This leads to the so-called semantic gap, between the semantics induced from the low-level features and the real high-level meaningful user interpretation of the image. To reduce this gap, relevance feedback has been adopted by most recent CBIR systems [8]. When relevance feedback is used, the search is considered an iterative process in which the original query is refined interactively, to progressively obtain a more accurate result. At each iteration, the system retrieves a series of images according to a predefined similarity measure, and requires user interaction to mark the relevant and non-relevant retrievals. This data is used to modify some system parameters and produce a new set of results, repeating the process until a satisfying enough result is obtained. In this context, the relationship between any image in the database and the user's desire is usually expressed in terms of a relevance value. This value is aimed at directly reflecting the interest that the user may have in the image and is to be refined at each iteration.

Most relevance feedback algorithms use the user's selection to search for global properties, which are shared by the relevant samples available at each iteration [8]. From a Pattern Recognition viewpoint, this can be seen as obtaining an appropriate estimate of the probability of (subjective) relevance. Many different approaches exist to model and progressively refine these estimates. However, relevance feedback faces a small sample problem whose models cannot be reliably established because of the semantic gap. In this context, nonparametric distance based methods using neighbours are particularly appealing [9], [10], [11], [12]. The aim of these methods is to assess relevance of a given image by using distances to relevant and non-relevant neighbours. In particular, an image is considered as much relevant as its distance from the nearest relevant image is small compared to the distance of its nearest non-relevant image.

II. MOTIVATION

- A query is represented by a single point in a feature space and refinement process attempts to reformulate query vector so that it is closer to the space containing the relevant images. With the assumption of the unimodality of relevant images, the optimal query maximizes similarity to relevant images and minimizes similarity to irrelevant ones
- Instead of using the single point query, multi-point query can be better choice to enhancing the performance of CBIR
- Query point movement is limited by a constraint of unimodality in taking into account the user feedbacks. Query expansion gives better results than query point movement, but it cannot take into account irrelevant images from the user feedbacks. Combination of two popular techniques of relevance feedback: query point movement and query expansion.

III. LITERATURE REVIEW

Many works have been proposed by researchers for content-based image retrieval. A brief review of some of the recent researches is presented here.

T. M. Deserno *et al.* [13] have presented a more systematic and comprehensive view of the concept of "gaps" in medical CBIR research. They have defined an ontology of 14 gaps that addresses the image content and features, as well as system performance and usability. Also they have identified seven system characteristics that impact CBIR applicability and performance. They have presented a framework. It can be used posteriori to compare medical CBIR systems and approaches for specific biomedical image domains and goals and a priori during the design phase of a medical CBIR application, as the systematic analysis of gaps provides detailed insight in system comparison and helps to direct future research.

Daekeun You *et al.* [14] have proposed a model in which detecting arrows, pointers, and other annotations such as text labels, can be very beneficial in locating regions of interest within figures in biomedical articles. Such annotations can be identified through relevant text snippet analysis (captions, figure mentions in the article text), image analysis methods are necessary to identify location of the symbols in the figure images. Identifying these and the image content annotated can be valuable for improved biomedical retrieval. This was achieved by attaching biomedical concepts extracted from caption and mention text analysis to image features computed at the image ROIs annotated by these symbols. Such tagging can help improve image indexing quality and subsequently the indexing and retrieval of biomedical articles through both text-based retrieval methods as well as content-based image retrieval.

Ryan McDonald *et al.* [15] have proposed a classifier was designed specifically to be readily adaptable to a wide domain of knowledge. For the identification of articles potentially mentioning genomic variations or mutations of a specific gene, the system requires only: 1) the classifier; 2) a set of training articles or abstracts that contain both positive and negative instances of the type of genomic mention of interest; and 3) genomic variation tagger. Preliminary results shown that performance was slightly but not substantially improved with the addition of the tagger. Furthermore, the classifier can be trained upon any set of documents in which a contextual distinction can be made, although the performance will likely vary depending upon how precisely the distinction between positive and negative instances can be defined.

Manabu Torii and Hongfang Liu [16] have proposed a simple and easy-to-deploy classifier ensemble approach for biomedical document classification/retrieval tasks. Constituent classifiers were built by varying the sizes of the feature set for an ML algorithm. When a single classifier was employed in a database curation project, a number of classifiers with different sizes of feature sets would be built anyway before the best performing system was selected. The proposed approach suggested combining such intermediate classifiers. In their experiments, SVM ensembles outperformed all the constituent classifiers in terms of both AUC and BEP. Using this approach, they updated the classification performance previously reported on the benchmarking data sets, and set new baseline performance for the data sets. However, the ensemble approach was not effective when there was no sufficient data to train reliable constituent classifiers or when it was applied to Naïve Bayes classifiers.

Beibei Cheng *et al.* [17] have proposed a model in which figure image segmentation is an important and necessary first step in annotating images for improved information retrieval for clinical decision support. This step helps subsequent image annotation and CBIR methods perform optimally. For accurate sub-figure image segmentation first need to detect the image type. Regular images usually provide a strong inter-panel boundary which is used to detect the sub-figure panels. Finding subfigure panels in illustration images is more challenging.

Daekeun You *et al.* [18] have proposed a model in which authors frequently use pointers and symbols to highlight specific local regions and mention them in figure captions and text discussions. Localizing those pointers can help extract specific local regions of interest (ROIs) and using the ROIs could improve relevance quality of conventional retrieval approaches by combining textual and image features from local regions. Region growing technique was applied to improve pointer segmentation and ROI extraction performance. Active Shape Model (ASM)-based pointer recognizer was developed to handle pointers that cannot be recognized by the MRF recognizer due to some distortion in their boundary. Average 87% success rate on pointer recognition was achieved.

A. Jain *et al.* [19] have presented an algorithm for retrieving images with respect to a database consisting of engineering/computer-aided design (CAD) models. The algorithm used the shape information in an image along with its 3D information. A linear approximation procedure that can capture the depth information using the idea of shape from shading has been used. After that Retrieval of objects was done using a similarity measure that combines shape and the depth information. Plotted precision/recall curves showed that this methodology was very effective for an engineering database.

IV. METHODOLOGY

Clusters-Based Combination of Query Movement and Query Expansion for Content Based Image Retrieval:

As shown in the Figure 4.1, a huge database of images is considered. The feature descriptor of the pictures in the database has to be taken out from it. A vector is created based upon the feature descriptor extracted from the picture and it is called as feature vector.

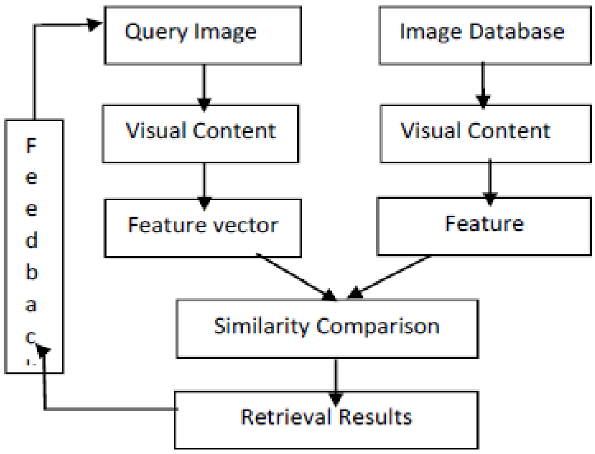

Fig.4.1 Block Diagram of CBIR

In this Research, a novel method of combining the two techniques is proposed for query by example in CBIR. Query expansion is used to construct multipoint queries by clustering the relevant images. Query point movement is used to improve the representation of the multiple point queries by applying the Rocchio's technique on the relevant and the irrelevant images. Our contribution is a cluster-based relevance feedback technique, which uses the query point movement technique and the irrelevant examples to enhance the efficiency of query expansion.

4.1 Query and Expansion

Most content-based multimedia retrieval systems support a query by example model. However, the user may not be able to find a good example to represent his information needed. In this case, a system that relies only on the example provided by the user at the beginning will limit the user's ability to choose the right image as an example. Query expansion overcomes this limitation by adding relevant information to the query and drop less relevant one [20] [21]. Let $Z = \{z_1, z_2, ..., z_{N_{img}}\}$ denote the identity of images in the image database. Let $X = \{x_1, x_2, ..., x_{N_{img}}\}$ denote the image database, where each xi is a vector that contains the low-level features of the image zi. Let $R = \{r_1, r_2, ..., r_{N_{img}}\}$ denote the log data in the log database, where each r_i contains relevance judgments in the i^{th} log session. Let $L = \{(z_1, y_1), (z_2, y_2), ..., (z_{N_l}, y_{N_l})\}$ be the collection of labeled images acquired through the online feedback for a user. According to the Log-Based Relevance Feedback, both the low-level features of the image content, i.e., X, and the log data of users' feedback, i.e., R, should be included to determine the relevance function f_q. Meanwhile, to reduce the number of iterations of online relevance feedback, a good learning algorithm should require only a small number of labeled image examples from the online relevance feedback, i.e., $|L|$.Given that the relevance function depends on both R and X, a simple strategy is to first learn a relevance function for each of these two types of information, and then combine them through a unified scheme. Let $f_R(z_i)$ denote a relevance function based on the log data of users' feedback and $f_X(z_i)$ denote a relevance function based on the low level features of the image content. Both of them are normalized to [0, 1], respectively. Then, the overall relevance function can be the combination of these two functions as follows:

$$f_q(z_i) = \frac{1}{2}(f_R(z_i) + f_X(z_i)) \qquad (4.1)$$

In the following, we will describe how to acquire the relevance functions $f_q(z_i)$ and $f_X(z_i)$ separately.

Let us first consider the log data of users' feedback. When two images have similar content, we would expect different users to express similar relevance judgements for these two images. On the other hand, for two images with dramatically different content, there should be no correlation in their relevance judgments in log data. Hence, to estimate the similarity between two images z_i and z_j, we suggest a modified correlation function to measure their relevance judgments in the log data, i.e.,

$$c_{i,j} = \sum_k \delta_{k,i,j} \cdot r_{k,i} \cdot r_{k,j} \qquad (4.2)$$

where $\delta_{k,i,j}$ is defined as follows:

$$\delta_{k,i,j} = \begin{cases} 1 \; if \; r_{k,i} + r_{k,j} \geq 0 \\ 0 \; if \; r_{k,i} + r_{k,j} < 0, \end{cases} \qquad (4.3)$$

Note that $\delta_{k,i,j}$ is engaged to remove (-1,-1) pairs among ($r_{k,i}, r_{k,j}$) in the computation of similarity. This is because it is difficult to judge the similarity of two images when they both are marked as "irrelevant" to users' information needs. Evidently, image z_i and image z_j are relevant when c_{ij} is positive, irrelevant when c_{ij} is negative. When c_{ij} is around zero, it is usually hard to judge if one image is relevant to the other.Based on the above similarity function, we can develop the relevance function based on the log data. Let L^+ denote the set of positive (or relevant) images in L, and L^- denote the set of negative (or irrelevant) samples. For an image in the database, we compute its overall similarities to both positive and negative images, and the difference between these two similarities will indicate the relevance of the image to the user's query. More specifically, the overall relevance function can be formulated as follows:

$$f_R(z_i) = \max_{k \in L^+} \left\{ \frac{c_{k,i}}{\max_j c_{k,j}} \right\} - \max_{k \in L^-} \left\{ \frac{c_{k,i}}{\max_j c_{k,j}} \right\} \qquad (4.4)$$

Despite its simple form, our empirical studies have shown that the above relevance function is effective in practice.

4.2 Query Point Movement

Query point movement [22], [23] is referred to as the retrieval by single point query, which is modified via relevant and irrelevant images with the assumption of the unimodality of relevant images [24]. Unimodality means that all relevant images are similar between them and they form a distinct cluster from other images in the feature space. The query point movement tries to archive the ideal query point by moving it towards relevant images and away from irrelevant ones [25]. It is essentially tries to improve the estimate of the 'ideal query point' by moving it towards good example points and away from bad example points. Query is represented by a single point in a feature space and refinement process attempts to move that point toward the direction where relevant points were located. The frequently used technique to iteratively improve this estimation is Rocchio's formula given bellow. This is technique implemented in the MARS system [26] [4].

$$q_{n+1} = \alpha q_n + \frac{\beta}{N + (n)} \sum_{j=1}^{J_{rel}} X_j - \frac{\gamma}{N - (n)} \sum_{J=1}^{J_{non\_rel}} Y_j \qquad (4.5)$$

where q_n is the query point for n^{th} round of the search cycle; parameters , α , β and γ suitable constants, also commonly known as the weight parameters. J_{rel} is the number of relevant images in X_j and J_{non_rel} is the total number of non-relevant images in Y_j. Depending on the nature of the data samples, the parameters β and γ can be adjusted to be more biased towards one sample group. It should be noted that the negative sample may totally ignored if variable γ is set to zero, and the history of the query point can also be disregarded by setting variable α to zero [4].

4.3 Combination of Query Movement and Query Expansion Based on Clustering

The main disadvantage of query point movement is the constraint of unimodality on relevant examples and the main disadvantage of the query expansion is the inability to make effective use of irrelevant images. Query point movement tries to move toward the relevant examples and get far from irrelevant ones. However, the ideal query point includes the irrelevant examples because of the unimodality of the relevant examples. In this section, a combination of query point movement and query expansion is presented. The query point movement technique is used to enhance the local clusters construction of the query expansion. The local clusters are calculated from the relevant examples by the query expansion technique then the irrelevant examples are used by the query point movement technique to move the local clusters toward the ideal query points. Each local cluster moves toward the ideal point quicker and the irrelevant examples are eliminated. Instead of calculating the query points, which cover all the relevant examples in each local cluster as in query expansion, here, query point moves toward the relevant examples and move far away irrelevant examples in each cluster. The query expansion technique does not use the irrelevant examples because we cannot cluster relevant and irrelevant examples together. By combining query movement and query expansion, which incorporates the irrelevant examples, is described below.

In the first iteration of relevance feedback, the single-point query is replaced by a multiple point query by using the query expansion technique. Then the relevant examples are clustered into c clusters. The parameter c is auto selected by the clustering algorithm, which is limited to a fixed maximum value. The irrelevant examples are then classified into these c clusters. The k Nearest Neighbors classifier (k-NN) is used because of its effectiveness and its simplicity; the parameter k of this classifier is selected through following equation (6).

$$k_i = \min\left(\left|C_j\right|, j = 1 : c\right) \quad (4.6)$$

Let J_{rel} denote total number of relevant examples and J_{non_rel} denote total number of irrelevant examples of the local cluster C_i. The query point $\vec{q}_i$ of this cluster is calculated using the query movement technique which is represented in the following equation (7).

$$\vec{q}_i = \frac{\sum_{j=1}^{J_{rel}} x_j}{J_{rel}} - \frac{\sum_{j=1}^{J_{non-rel}} x_j}{J_{non-rel}} \quad (4.7)$$

Then, the queries are updated through the following equation (4.8)

$$\vec{q}_{i+1} = \alpha\vec{q}_i + \frac{\beta}{|J_{rel}|}\sum_{x\in J_{rel}} \vec{x} - \frac{\gamma}{|J_{non-rel}|}\sum_{x\in J_{non-rel}} \vec{x} \quad (4.8)$$

V. RESULTS

In this paper, the result is shown in the form of the output got for every input query image. There are five parameters calculated which are described as follows

Sensitivity: Sensitivity relates to the test's ability to correctly detect patients who do have a condition. Consider the example of a medical test used to identify a disease. Sensitivity of the test is the proportion of people known to have the disease, who test positive for it.

Specificity: Specificity relates to the test's ability to correctly detect patients without a condition. Consider the example of a medical test for diagnosing a disease. Specificity of a test is the proportion of healthy patients known not to have the disease, who will test negative for it.

Accuracy: Accuracy is also used as a statistical measure of how well a binary classification test correctly identifies or excludes a condition.

5.1 Experimental Results 1

The first experiment is done in a multimedia-based real-world image and the metrics such as precision and Response time are calculated. An image database from MIT Media Laboratories is used for the simulation and result verification. Out of 2000 images, 500 images are selected and manually grouped and properly labeled in to 5 classes.

This set of 500 images is used as initial database. The Images are manually grouped in to the five groups viz. 1.Coast Images, 2.Forest Images, 3Mounain Images, 4.Open country Images and 5.Tall building Images.

1. The effectiveness and accuracy of classification and retrieval of the Image. The precision of querying based on the feature vectors extracted; the higher the system's precision, the higher the percentage of matching images returned to a query.
2. The speed of the Classification and Retrieval of the Image .It is desirable to have as lowest as possible the elapsed time for both

Fig.5.1Multimedia query image

Fig 5..2 Retrieved image sample1

Fig.5.3 Retrieved image sample2

Fig.5.4 Retrieved image sample3

The sample retrieval process of the multimedia image retrieval is shown in fig.1, 2, 3, and 4. For the evaluation, the following Equation is used for precision.

$$\text{Precision} = \frac{\text{No. of correct images retrieved}}{\text{No. of total images retrieved}} \times 100$$

The results shown in the table.5.1, by using this proposed method is possible to accurately retrieve the Query Image from the given database. However, the Response time should also be considered for the further improvement.

Table.5.1 Calculation of precision and response time

S.No	Class of the image	Precision In %	Response time in secs
1	Coast	99.86	23.372030
2	Coast	99.99	43.355776
3	Forest	99.81	54.219515
4	Mountains	100%	33.191574
5	Mountains	100%	13.85094
6	Open country	100%	43.223969
7	Tall buildings	100%	37.232646

5.2 Experimental Results 2

The medical images are analyzed in this section with the addition of multimedia images.

Figure.6 shows the set of images retrieved from a Google image search operation performed using the query image shown in fig. 5, a conventional brain MRI slice, as the sample input image. It will be noted that while some images matched well to the source image, others do not match at all.

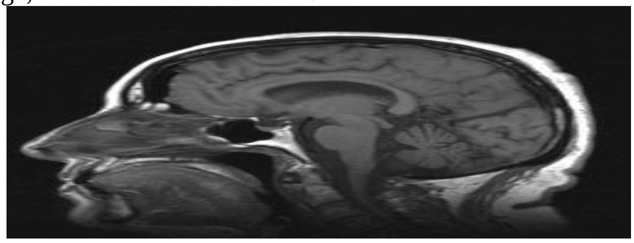

Fig. 5.5 Medical query image (MRI-Brain)

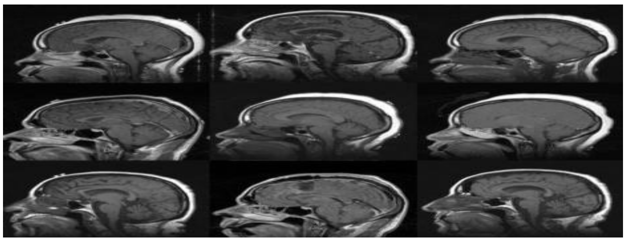

Fig.5. 6 Retrieved medical images (i1-i9)

The fig. 5.6 consist of nine forms of samples, retrieved from the above query image and each image is denoted as i1, i2, i3…i9 etc, from which the similarity measurement is taken.

Table.5.2Similarity measurement table

Image sets	Similarity measure
i1	151266
i2	150770
i3	131276
i4	146162
i5	104035
i6	811103
i7	102067
i8	784450
i9	138519

Table.5.2 shows an example of similarity values for the statistical measure block Mean, calculated using a block size of 8x8 pixels. The values shown are the normalized sum of differences of all corresponding pairs of blocks Means in the two images. From this data it can be seen that images i7 and i5 are the most similar to the query image, but the next ranked images are not highly distinctive in similarity. Images i6 and i8 are the least similar to i0, and differ considerably from the remainder of the images in this characteristic.

5.3 Experimental results 3

In this part, the accuracy, sensitivity and specificity are calculated for both the multimedia and medical images.

Table.5.3 Comparative Analysis based on Accuracy, Sensitivity and Specificity

	Type of image	**Accuracy**	**Sensitivity**	**Specificity**
Proposed Methodology	Multimedia Image	0.9592	0.4000	1
	Medical image	0.9692	0.4800	1
Query Expansion	Multimedia image	0.8239	0.3535	0.88
	Medical image	0.8526	0.3890	0.91
Query Point Movement	Multimedia image	0.8319	0.3835	0.90
	Medical image	0.8692	0.4150	0.93

Query expansion and query point movement of the proposed methodology is compared based on the type of images with respect to accuracy, sensitivity, specificity for the evaluation of the introduced mechanism shown in table.5.3

Table5. 4 Comparative Analysis based on MSE and PSNR

	Type OF Image	**MSE**	**PSNR**
Proposed Methodology	Multimedia image	0.157288	60.271
	Medical image	0.00675422	68.7179
Query Expansion	Multimedia image	0.25874	42.3248
	Medical image	0.11692	55.5681
Query Point Movement	Multimedia image	0.9592	45.6581
	Medical image	0.9692	59.9548

Query expansion and query point movement of the proposed methodology is also compared based on the type of images with respect to MSE and PSNR value as mentioned in the above table.5.4

In this section the results are shown in the form of the output got for every input query image. There are two parameters calculated. They are:

a. MSE – It is the mean square error. It is defined on a monochrome noise-free image as

$$MSE = \frac{1}{m\,n}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}[I(i,j) - K(i,j)]^2 \quad \text{---------------(5.1)}$$

b. PSNR – It is the peak signal to noise ratio. It is expressed in logarithmic decibel. It is best defined via MSE as

$$PSNR = 10 \cdot \log_{10}\left(\frac{MAX_I^2}{MSE}\right) \text{----(5.2)-} \quad = 20 \cdot \log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \text{------------(5.3)}$$

$$= 20 \cdot \log_{10}(MAX_I) - 10 \cdot \log_{10}(MSE) \quad \text{----------(5.4)}$$

where MAX is the maximum possible pixel value in an image. It is 255 for an 8 bit image. These two values are displayed just below every image. The comparison is done with the query image for these parameters also. Experimental results 1 and 2 are the outputs obtained for multimedia images. Experimental result 3 gives the output obtained for medical images. The GUI contains the query image, the output images obtained as a result of performing CBIR, normalized correlation graph and the normalized Euclidean distance for colour histogram. The output images can be viewed separately by clicking 'VIEW'.

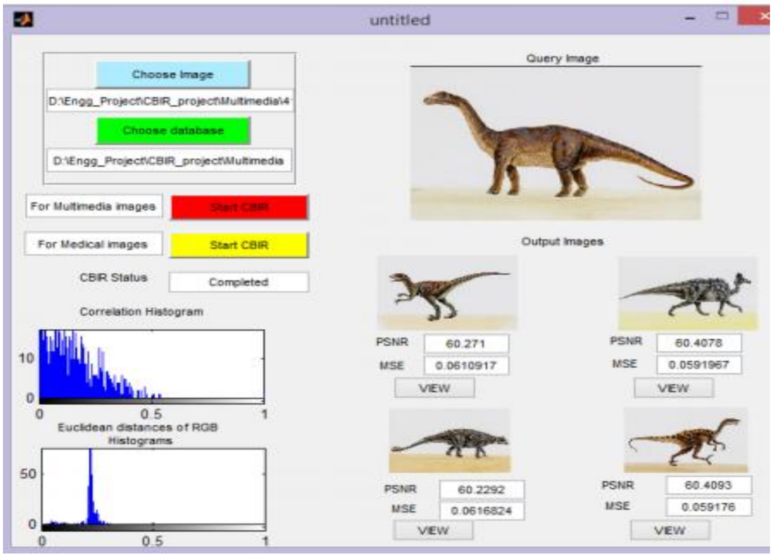

Fig 5.7 Experimental result for multimedia-1

Fig 5,8 Experimental result for multimedia -2

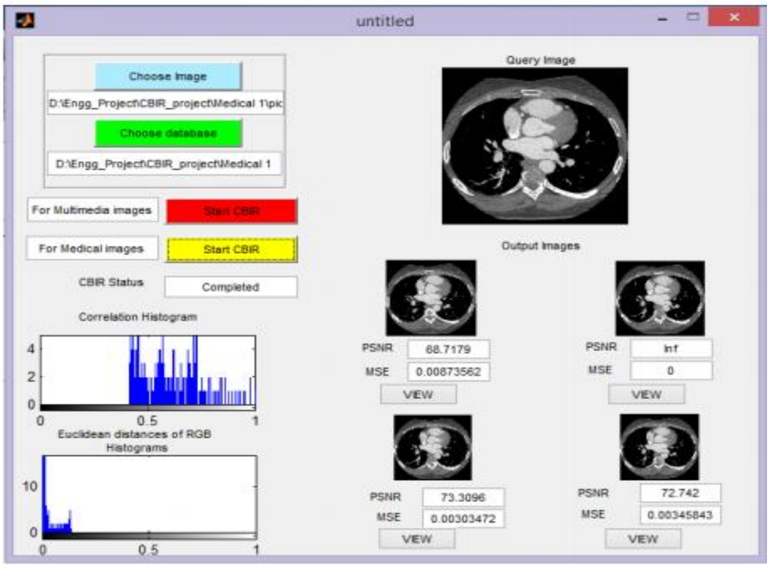

Fig 5.9 Experimental result or medical image 1

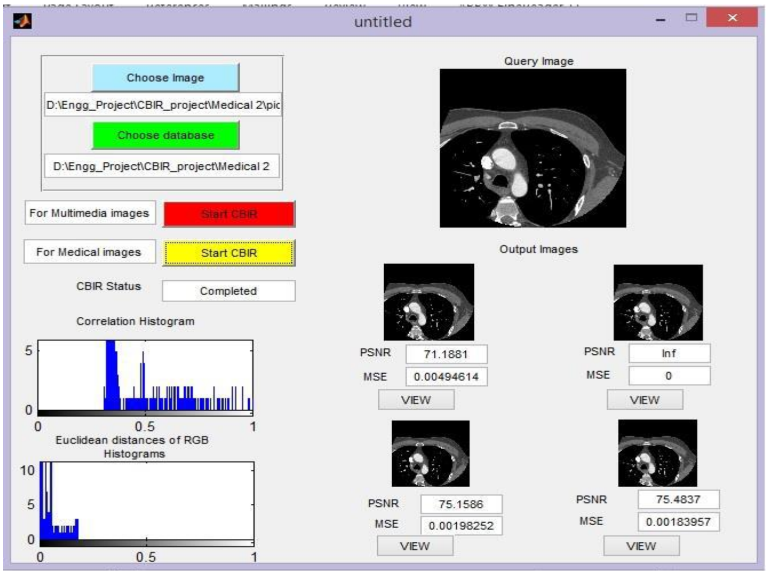

Fig 5.10 Experimental result medical image 2

5.4 Experimental results 4

In this paper the experiment is carried on to examine the performance and efficiency of the system that has been proposed using the WANG database. This database with 1000 images as shown in figure 5.11 with 10 clusters is one of the benchmark database for the content based image retrieval systems[7]. According to the literature survey the main parameter that are calculated in the CBIR is average precision. The various parameters like Average Precision, Recall, Sensitivity, Specificity etc. shows the performance of the proposed method.

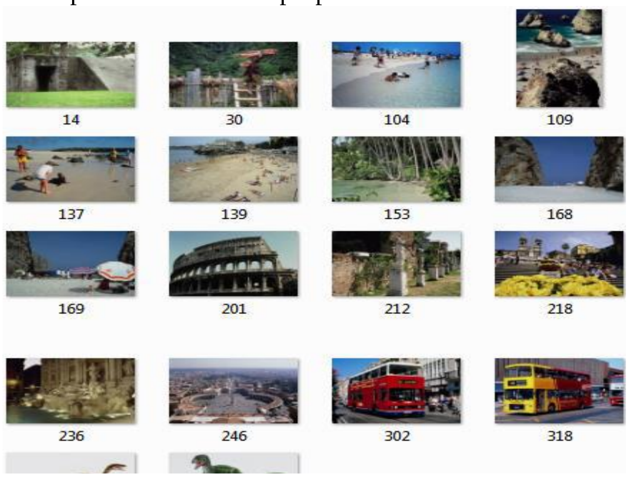

Figure 5.11: WANG Database - 1000 Image

As explained earlier, the retrieval system always retrieves the images based on the query image features. So the important step here is to give the query image. Few query images are stored in other folder which are used during giving the reference image. This is shown in the figure 5.12. The query image given to the system is 315.jpg.

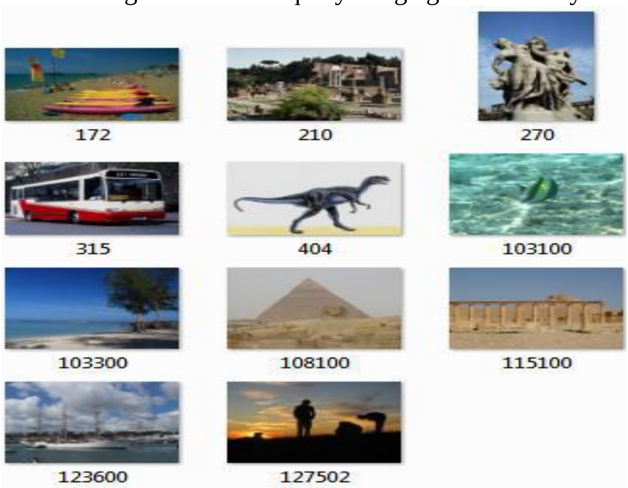

Figure 5.12: Query Images

Figure 5.13: Query Image

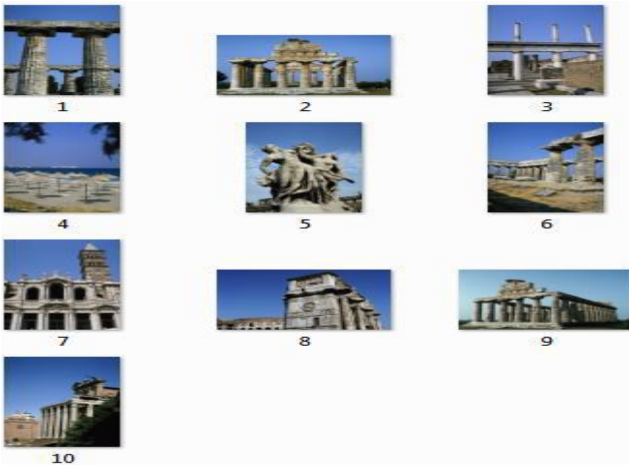

Figure 5.14: Retrieved images from the database.

For the query image in figure 5.12 the retrieved results are shown in figure 5.14. This method is checked for various images and the performance evaluation for our system is given in the next section.

VI. CONCLUSION

In this paper, the cluster-based relevance feedback is proposed with two different approaches: the clustering-repeat and the clustering-no-repeat. Our method combines the two query modification methods, query point movement and query expansion, to take advantage the irrelevant examples and advantages of both traditional techniques, our method gives better results. Our method does not require complex computations, but offers very significant improvements in accuracy compared to traditional techniques. As the relevance, feedback methods presented here are valid for both text and image retrieval, we are planning, in the near future, to extend our cluster-based relevance feedback by combining text-based and content based image retrieval. To achieve this, a text/image learning model is needed and can be built onto the same relevance feedback model. This learning model would be considered as long-term memory relevance feedback.

VII. FUTURE SCOPE

Content-based medical and multimedia image retrieval schemes presented in this research are promising and there is significant scope for future research.This work improves the understanding of knowledge from various techniques that promotes feature extraction and similarity measurement, which aids medical image retrieval and advances the visual access through its contributions. The fine-tuning of images may be done in future by adding some shape and color features in the enhanced manner with the help of the application of our research algorithm used with multimodal feature sets. Different soft computing methods may also be used to select trivial feature sets from the algorithm to extend this in web-based or internet applications.The system can be further employed as online media based search engine that can search images and well as media files, both audio and video based on the contents of the query file given in this research.

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