Fractals Based Clustering for CBIR

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Abstract— **Fractal based CBIR is based on the self similarity fundamentals of fractals. Mathematical and natural fractals are the shapes whose roughness and fragmentation neither tend to vanish, nor fluctuate, but remain essentially unchanged as one zooms in continually and examination is refined. Since an image can be characterized by its fractal code, a fractal code can therefore be used as a signature of the image. Image clustering supports the hypothesis that semantically similar images tend to be clustered in some feature space. The meaningful clustering is in pursuit of search for nearest neighbor in terms of similarity of the images. The objective of this work is to evaluate the use of fractal dimension as a quantitative index and effectiveness of clustering approach for image retrieval mechanism. The image retrieval mechanism has been implemented using clustering and Hausdorff dimension based fractals so as to combine the advantages of both the approaches. The results are encouraging enough to investigate use of fractals for CBIR.**

Keywords- *Content based image retrieval (CBIR), Hausdorff dimension, Clustering, Maxdistance, Maxclustersize, Recall and Precision*

I. INTRODUCTION

Content Based Image Retrieval [1] has been approached through multiple ways to address various facets of image retrieval. Some of the valued research objectives have been around retrieval time, handling large databases, feature vector extraction [2], length of the feature vector, principle components [3], precision, recall, query image format and understanding user intent. The significant step in a CBIR is extraction of features of an image which can then be used for comparison and retrieval. The extracted features are compared with feature vector [4] of query image for establishing similarity between images as a part of the retrieval procedure. These features precisely describe the contents of the image. Therefore a rich feature set is expected out of the image. These features have to be discriminative and sufficient for the description of the image. The issue is significant when images are similar. An all feature inclusive feature vector has always been a challenge in the image retrieval process.

Approaches that have been extensively used include working with color, texture, shape and their derivatives. Most of the retrieval techniques like Block Truncation Coding [5], colour histograms, edge descriptors, shape features, texture features, Fourier descriptors, local binary patterns, colour coherence vector, wavelets, and Tahoma features are in a way sub sets of colour, texture and shape. Compressed domain [6] images throw a different challenge. Localized features can also be significant. Fractals or multifractals have been rarely used for CBIR. Use of fractals for CBIR is thus a distinct approach wherein a single value fractal becomes the feature vector of the image. The approach taken in this paper is also distinct because fractals have not been combined with image clustering for image retrieval. The objective of the proposed algorithm is to evaluate new approach of forming clusters and further evaluating CBIR

1) Number of clusters for the given maxclustersize
2) Number of clusters formed for the given maxdistance
3) Effect of maxclustersize and maxdistance on recall and precision

The rest of the paper is organized as follows. Section 2 briefs on the literature survey and captures few of the approaches for CBIR. Section 3 explains the proposed approach on CBIR system. Performance Analysis and experimental results has been discussed in section 4. Experimental results and performance analysis has been are presented in section 4. Conclusions are discussed in section 5.

II. LITERATURE SURVEY

Digital images are being used for a variety of applications in the information technology enabled operations. Identity cards, Passports, National Personal Identification Systems, Public Distribution Systems, and Forensics are just few examples of the same. Search for a specific image has to be through texture analysis [7], annotation, some indexing mechanism [8] or a search engine. Such applications combined with the use of internet and digital technologies have laid the foundation for need of an effective CBIR system. Color histogram and gradient matching based techniques have been extensively tried and yielded good results. Color information of an image provides the best possible information of the image. Vector Quantization [9], Wavelets [10], and hybrid [11] approaches have been also pursued with some good results. Clustering [12] [13] has been tried to speed up the retrieval process. Shape of an image is equally another vital parameter for image retrieval and has been successfully tried with Sobel, Canny, Roberts and other operators. Texture, Tahoma features, Relevance Feedback, picture self organizing maps, Fourier descriptors, color coherence vector and Eigen images, are some of the efforts in CBIR. The feature vector extraction methodology and feature vector size have a deep influence on the results of the retrieval process. Use of fractals [14] [15] can be an innovative approach. The retrieval process has been a trade off between feature vector size, retrieval time, accuracy, database size and recall. Image clustering has been used to link similar images together so as to eliminate match with every image of database. However the typical issues with image clustering are feature extraction, organization of feature data and the methodology to classify an image to a cluster. Image clustering shall improve the quality and quantity of recommendation through results, and prove to be a genuine resolve for scalability of the solution. Hierarchical and K means clustering has been used by some researchers for image retrieval. Cluster architectures [16] hold the potential for large database image retrieval systems. Clustering will minimize internal communication within CBIR system. ImageRETRO [1] search engine developed by Department of Computer Science, University of Amsterdam, Netherlands, used clustering with colour features in image retrieval. MARS [1] (Multimedia Analysis and Retrieval System) search engine developed at University of California also used clustering technique along with colour histograms.

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III. CBIR SYSTEM DEVELOPMENT

The proposed fractal based clustering system has used fractals, Hausdorff dimension, to compute a single digit feature vector of the image and is then clubbed with image clustering approach for image retrieval.
The fractal based clustering approach for CBIR has been implemented in two steps as shown in Fig 3.1:

a) Off line Phase
b) Online Phase

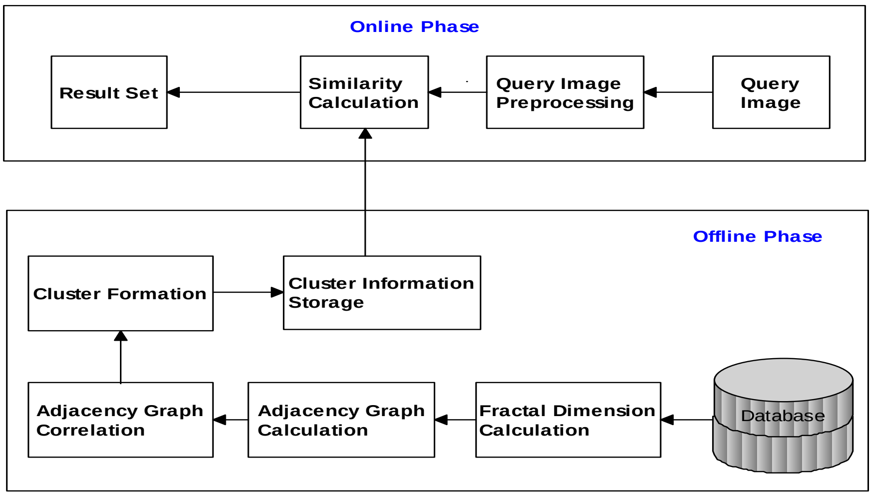

Fig 3.1 Fractals based Clustering CBIR system.

A. *Offline Phase*

The significant steps in the offline phase are

1) Fractal dimension calculation
2) Adjacency graph computation

3) Cluster formation

For the given database, calculate the Hausdorff fractal dimension of every image. Images in the database are either 384 x 256 or 256 x 384 in size but are resized to 128 x 128 for further computation. The defining property of a fractal is self-similarity, which refers to an infinite nesting of structure on all scales. Strict self-similarity refers to a characteristic of a form exhibited when a substructure resembles a superstructure in the same form. All natural objects are fractals. All irregular trajectories based objects are fractals. A Hausdorff dimension is the mathematical expression of dimensions of the object. A fractal dimension is a ratio providing a statistical index of complexity comparing how detail in a pattern changes with the scale at which it is measured. A fractal dimension is greater than the dimension of the space containing it and does not have to be an integer.

Expressed mathematically, the property of the object, its length, area or volume noted N is related to its dimension D, by:

$N=r^D$..................................(1)

The Hausdorff dimension can be obtained by taking the logarithm on both sides of the equation and solving for D

$D=\log(N)/\log(r)$....................(2)

N can be considered as the number of self-similar objects created from the original object when it is divided by r. One of the essential features of the fractal is that its Hausdorff dimension exceeds its topological dimension. Hausdorff dimension is an extended non negative real number associated with any metric space. The Hausdorff dimension generalizes the notion of the dimension of the real vector space. The Hausdorff dimension of an n-dimensional inner product space equals n. Hausdorff dimension is also known as Hausdorff – Besicovitch dimension. Many irregular sets have non integer Hausdorff dimension. For shapes that are in line with geometrical shapes, smooth shapes, Hausdorff dimension is an integer. The following theorem deals with existence of fractals with given Hausdorff dimension in Euclidean spaces: Theorem: For any real $r \geq 0$ and integer $n \geq r$, there are continuum fractals with Hausdorff dimension r in n-dimensional Euclidean space. Fractal analysis is assessing fractal characteristic of data. Such an analysis is widely used to characterize properties of natural objects. Here an image is characterized through fractal analysis. Box counting technique has been used to compute the fractal dimension. It works by covering fractal with boxes and then evaluating the number of boxes required to cover fractal completely. In this experimentation, the box size selected is 128 x 128 and subsequently decreasing. We then decrease the box size by half as 64 x 64, 32 x 32 and then go up to 1 x1. The technique is repeated with different sizes of boxes to result in logarithmic function of box size and number of boxes to cover the fractal. The slope of this function is called box dimension or fractal dimension. Alternately, a polynomial equation of degree 1 (y=c1*x+c2) can be created to provide c1 as fractal dimension of an image.

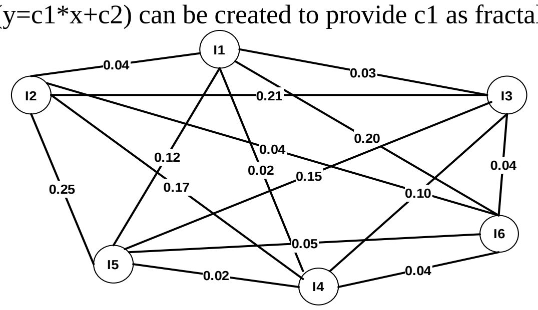

Fig 3.2 Fully Connected Graphs through ED

For graph creation, each image is considered as node of the graph. Based on the fractal dimension, generate the adjacency matrix through calculation of Euclidean distance of every image with respect to other. For each pair of image a and b, calculate d (a, b) which is degree of connectivity between images a and b where d (a, b) is the Euclidean distance which is given by equation:

$$d = \sqrt{(F_a - F_b)^2} \text{ .... } (3)$$

Where, F_a and F_b is fractal dimensions of images a and b respectively. Correlate the values with high distance between the images. If adjacency (I, J) > Maxdistance, then set it to max. This is the process through which image matching is identified. Then Depth First Search (DFS) is applied to generate the cluster. The graph is strongly connected graph as every vertex of the graph is connected to other vertex with some edge. Depth First Search is an algorithm for traversing or searching a tree or tree structure or graph. It begins with a node in the graph and then explores the entire graph for the unexplored ones. For cluster generation, the main parameter is maxclustersize. Figure 3.2 shows a fully connected graph created based on Euclidean distance between images. This step is establishes the correlation between the images. Similar images will tend to have minimum distance between them.

Figure 3.3 shows graph after elimination of edges greater than maxdistance. Such a step sets up the criteria for clustering.

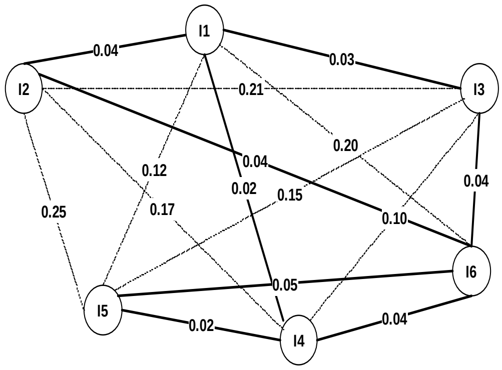

Fig3.3 Graphs after elimination of edges

The graph partitioning algorithms divide a graph into k disjoint partitions, such that the partitions are connected. Graph partitioning algorithm is utilized to search for groups of strongly connected images by partitioning the graph according to its connected components. Depth-first search (DFS) is an algorithm for traversing or searching a graph. Starting from a vertex a, DFS induced by M is applied to search for the connected component reachable from this vertex. Once the component has been found, the algorithm checks if there are any nodes that are not considered in the visit. If so, it means that a previously connected component has been split, and therefore, it needs to be identified. To do this, DFS is applied again by starting from one of the nodes that is not yet visited. In the worst case, when all the images are in the same cluster, the cost of this algorithm will be linear in terms of the number of edges in the complete graph G. Two main parameters must be accounted for while the algorithm is applied to the undirected graph. Maximum allowable Euclidian distance and Maximum cluster size are two parameters that significantly affect mining of cluster. Maxdistance is a maximum Euclidian distance parameter for filtering weights that are greater than constant value. The edges of the graph whose values are greater than Maxdistance are inadequately correlated and are thus not considered by the DFS graph search algorithm. DFS also considers the maximum cluster size, if there are still connected image but inclusion of that image causes to exceed the Maxclustersize then that image is neglected. It helps in decentralization of cluster. In this paper, the maximum cluster size is termed as Maxclustersize. But a cluster can contain fewer images than Maxclustersize

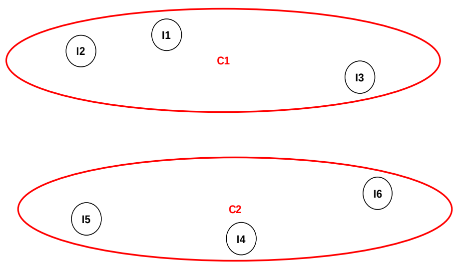

Fig 3.4 Cluster with maxclustersize = 3

Create cluster which contain Maxclustersize image. Search the adjacency matrix from first to last image, if Maxclustersize is not achieved. If adjacency (I, j) < maxdistance, then add image to cluster. Fig 3.4 displays the cluster formation with maxclustersize 3. One image can be part of only one cluster. Store the clusters into cluster array with cluster number and image number in particular cluster.

B. Online Phase

The online process involves following important tasks

1) Query Pre-processing
2) Cluster processing
3) Result Display

The offline process reduces the exhaustive task of comparing every image in the database with query image. Online processing task begins with accepting the query image. The query pre-processing requires resizing of the submitted query image to the size 128 x 128. Convert it to binary image to compute the fractal dimension. Hausdorff dimension has been assigned to every image of the image data base in the offline phase. Hausdorff dimension of the query image is computed and subjected for a image match from the database.

The computed Hausdorff dimension shall be the feature vector of the query image. Calculate the Euclidean distance of the query with respect to first image of every cluster. Find out minimum distance clusters in the set of clusters.

Choose clusters with highest similarity for result display. For more results display the clusters with next degree of similarity.

IV. PERFORMANCE ANALYSIS

The performance of the proposed CBIR system is validated on the system with listed features:
Processor: Intel Core i3
OS: Windows 7 Professional
Platform: MATLAB 7.8
RAM: 3 GB
Database: Wang database with 1000 images consisting of 10 categories with 100 images each

TABLE 1
FRACTAL DIMENSION OF AN IMAGE

Image					
Fractal Dimension	1.9004	1.8401	1.8980	1.9128	1.8833

Table 1 provides fractal dimensions of some reference images from the database used in this experimentation. Note that similar images have nearly same fractal dimension.
The results of the experimentation are given below. Cae1 and Case 2 are for a separate query image.
Case 1:

Fig 4.1 Query image

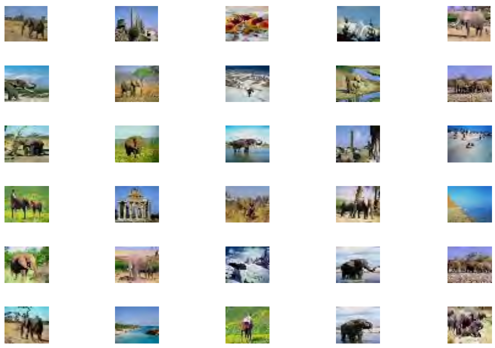

Fig 4.2 Results without clustering

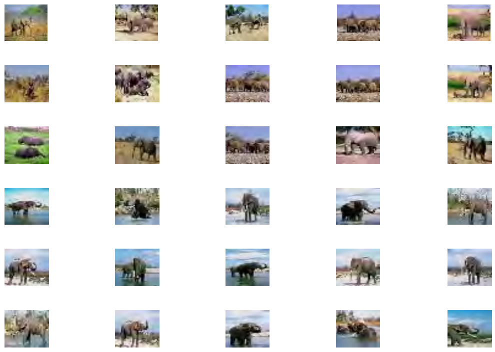

Fig 4.3 Results with clustering, maxclustersize of 15 and maxdistance 0.05

The fractal based clustering approach and the associated experimentation has demonstrated better results for a maxclustersize of 15 with 30 relevant images retrieved

Case 2:

Fig 4.4 Query Image

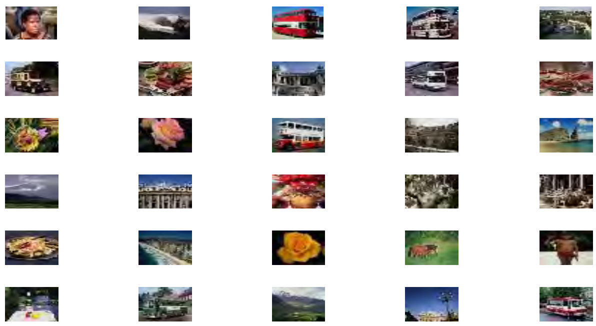

Fig 4.5 Results without Clustering

Fig 4.6 Results with clustering

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TABLE 2
EFFECT OF MAXCLUSTERSIZE

Max Cluster Size	No. of cluster formed	Relevant Images retrieved	Recall	Precision	Search Time (S)
5	208	25	0.25	0.83	1.034
10	110	20	0.20	0.66	1.024
15	80	30	0.30	1	1.019
20	62	11	0.11	0.36	1.024
25	50	18	0.18	0.60	1.020

There is enough evidence in results listed in Table 2 to state that with higher maxclustersize, number of clusters formed goes down and so also the number of relevant images retrieved. The main reason for such a response is that if the first image does not find a match, the entire cluster gets rejected from the results. Hence an optimum cluster size is a key to better results. Better results are displayed with cluster size of 15.
Similarly there shall be an optimum maxdistance for which the number of relevant images retrieved shall be more. Refer to Table 3 in which for maxdistance of 0.05 and 0.09, the number of relevant images retrieved are more. Accordingly, Precision and Recall shall be best at these optimum values of maxclustersize and maxdistance.

TABLE 3
EFFECT OF MAXDISTANCE

Max distance	No. of clusters formed	Relevant image retrieved	Recall	Precision	Search Time (S)
0.11	104	11	0.11	0.36	1.023
0.09	108	20	0.20	0.66	1.024
0.07	106	10	0.10	0.33	1.019
0.05	110	20	0.20	0.66	1.026
0.03	116	8	0.08	0.26	1.014
0.01	141	14	0.14	0.46	1.019
0.00	906	17	0.17	0.56	1.017

As the given query is going to be compared with first image of every cluster, the number of clusters that can be formed out of a database is of significant interest. Fig 4.7 validates the effect of maxclustersize on number of clusters formed. As entire cluster is going to be displayed as result, it is important that maxdistance and maxclustersize shall be optimally selected to get the best results. Fig 4.8 displays the effect of maxdistance on number of clusters formed. As demonstrated in the Fig 4.9, for a maxclustersize of 15, there is an improvement in Precision and Recall, where,

$$\text{Precision} = \frac{\text{No of relevant images retrieved}}{\text{Total number of images retrieved}} \qquad (4)$$

$$\text{Recall} = \frac{\text{No of relevant images retrieved}}{\text{Total number of relevant images in the Database}} \qquad (5)$$

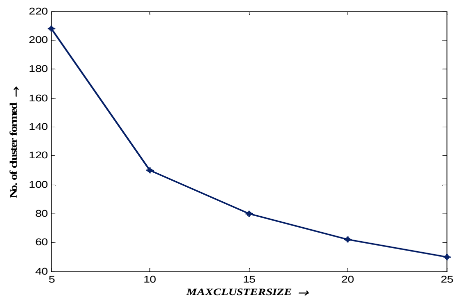

Fig 4.7 Effect of maxclustersize on number of clusters formed

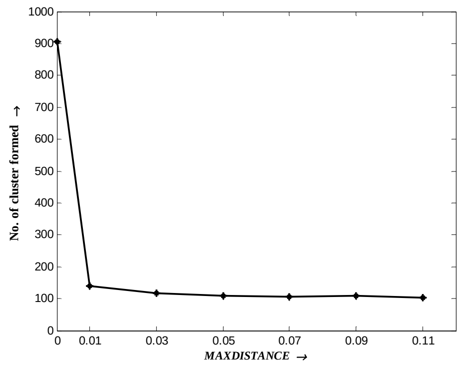

Fig 4.8 Effect of maxdistance on number of clusters formed

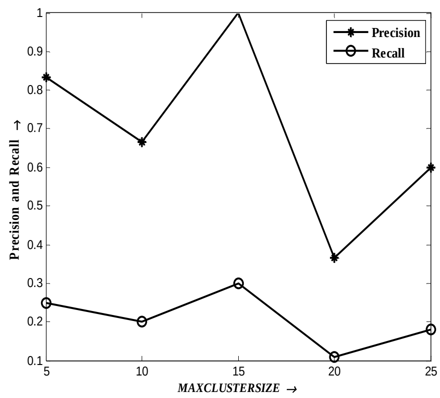

Fig 4.9 Effect of maxclustersize on precision and recall

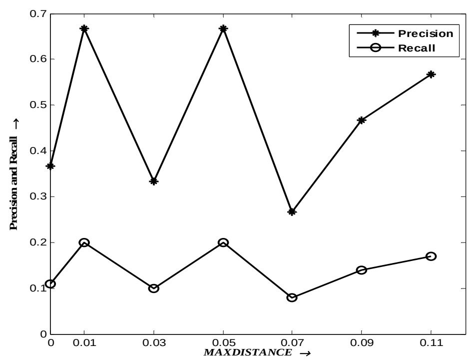

Fig 4.10 Effect of maxdistance on Recall and Precision

Fig 4.10 reflects the effect of maxdistance on Recall and Precision. As expected, as the maxdistance increases, there is a dip in precision and recall. For an optimum value of .05, results have been best.
The performance of the proposed fractal based clustering approach can also be analysed in comparison with system not using clustering approach. Without following clustering approach, for the same query image, the system retrieved 17 similar images at a recall of 0.56 and precision of 0.17.

TABLE 3
SEARCH TIME RESULTS

	Clustering (Sec)	Without Clustering (Sec)
Case 1	0.64	0.66
Case 2	0.64	0.68
Case 3	0.64	0.66

Table 3 displays the results obtained for three different cases with a query image each.. Hausdorff dimension based clustering not only helped to average out search time for all the query images but also brought down the search time. The results for Case 1 and Case 2 have been displayed in this paper for analysis. The retrieval time has improved with clustering approach. Maxdistance based clustering has proved to be a significant step as it has allowed to group similar images together. Fractal numbers computed for similar images have shown proximity through the generated numbers.

V CONCLUSIONS

Fractal dimension assisted content based image retrieval has the advantage of reduced calculations to work out feature vector of the image thereby significantly influencing retrieval time. Major advantage of Hausdorff distance based matching approach is it does not require point to point correspondences between two images. Clustering approach will link similar images together for the given database. For a given database size, there shall be an optimum maxclustersize for which the number of relevant images retrieved will be maximum. For the given cluster, only the first image shall be compared with query image. Such an approach reduces the complex task of comparing feature vector of all the images in the database. For large databases, retrieval time can be effectively reduced by clustering approach. The obtained results recommend the use of clustering approach to reduce the retrieval times. The obtained results encourage further investigations in the fractals combined with clustering approach for CBIR with more databases and hybrid approaches.

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