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Content Bases Image Search And Retrieval Using Indexing By KMeans Clustering Technique

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Abstract: With the popularity of network and development of multimedia technology, the traditional information retrieval techniques are not working efficiently according to users demand in searching and retrieving images from database. Recently the content based image retrieval concept becomes the hot topic in information retrieval domain. Due to the demand of information retrieval technique for image retrieval research has focused on content based image retrieval method. In today's world there is increased need of content based image retrieval technique in number of different domains such as education, medical imaging, crime prevention, whether forecasting, remote sensing and management of earth resources. Content based image retrieval (CBIR) deals with retrieval of relevant images from the large image database. It works on the features of images like color and texture. In our system we are proposing an enhancement to basic content based image retrieval technique with indexing support by using K-means clustering data mining technique. The enhanced feature helps in retrieving images from large database fastly. In this system an index is applied on database of images based on clustering technique. During this process clustering concept uses features like texture, color, shape, relevance feedback and wavelet based histogram method to find similarity among the images. Based on similarity value the images are divided into clusters, then the new image which is to be verified with database is compared with these clusters and based on its similarity corresponding images in cluster are retrieved.

Keywords: Image retrieval, clustering, color, texture, histogram, similarity matching, semantic similarity, K-means.

I. INTRODUCTION

Content based image retrieval is well known technology being used for the retrieval of images from large database. This image retrieval is a challenging topic that has been a research focus from many years. This has proven very much important because of its applications like face recognization, fingerprint recognization, pattern matching, verification and validation of images. The image retrieval is also called image classification in large database systems. In the past few years , there has been tremendous growth in database technology to store and retrieve large number of images. This requirement creates a demand for software systems for effective fast image retrieval from large database systems .The demand and use of multimedia applications in present world creates the need of content based image search and retrieval. The term content based image retrieval(CBIR) is originated by Kato from his work to retrieve images from database based on color and shape .Since then onwards the term CBIR is used for the process of searching and retrieving desired image from collection of database based on synthetical image features like color, texture and shape. The content based image retrieval is an important application in medical field which is used to permit radiologist to retrieve images of similar features for input image that lead to similar diagnosis.

The concept of CBIR (content based image retrieval) is explained using following diagram

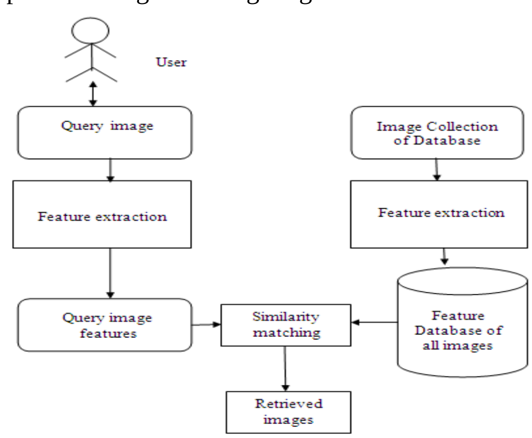

Fig1: Concept of CBIR

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Every CBIR system needs to have a module for feature extraction. This module is applied on query image and as well as on database of images. This module converts image into binary form and finds its features like shape, color, texture then it contains another module called similarity matching which is used to compare the input image features with features of database images. To find the features of image, the image is converted into wavelet histogram which is in binary matrix. For this we have a technique called haar wavelet.

A. **Color spaces**

Color spaces are important component in representing images in digital form. Color is usually represented by color histogram, color coherence vector which are combinedly called as color space. The color histogram feature is most important in image retrieval. Here color histogram is a vector which is collection of element where each element represents no of pixels in a bin of image.

B. **Texture**

It is another important feature generally used in similarity matching of images. Texture means smoothness, coarseness and regularity. The texture features are analyzed using statistical approach. In our proposed system we proposed to implement content. based image retrieval system with determining support. Here we are using K-means clustering technique of data mining to create index of images in database once index is created we implement retrieval and search process using index. Generally in traditional image search and retrieval process every time if we search a query image against database then the query image is verified with every image in database. During this process feature extraction is performed for query images and database images in every search process. Similarly, similarity matching is also performed in every search process. Thus the search process is costly and time consuming every time. In case of proposed system, first K-means clustering creates index and images are organized in clusters in memory. Every cluster is collection of similar images based on content. Now every time search process is implemented the feature extraction and similarity matching are performed on clusters rather than individual images. This proves the process is improved and less cost than traditional one.

II. Related Work

Lin et al. [14] proposed a color-texture and color-histogram based image retrieval system (CTCHIR). They proposed (1) three image features, based on color, texture and color distribution, as color co-occurrence matrix (CCM), difference between pixels of scan pattern (DBPSP) and color histogram for K-mean (CHKM) respectively and (2) a method for image retrieval by integrating CCM, DBPSP and CHKM to enhance image detection rate and simplify computation of image retrieval. From the experimental results they found that, their proposed method outperforms the Jhanwar et al. [33] and Hung and Dai [34] methods. Raghupathi et al. [35] have made a comparative study on image retrieval techniques, using different feature extraction methods like color histogram, Gabor Transform, color histogram + gabour transform, Contourlet Transform and color histogram + contourlet transform. Hiremath and Pujari [36] proposed CBIR system based on the color, texture and shape features by partitioning the image into tiles. The features computed on tiles serve as local descriptors of color and texture features. The color and texture analysis are analyzed by using two level grid frameworks and the shape feature is used by using Gradient Vector Flow. The comparison of experimental result of proposed method with other system [37]-[40] found that, their proposed retrieval system gives better performance than the others. Rao et al. [41] proposed CTDCIRS (color-texture and dominant color based image retrieval system), they integrated three features like Motif co occurrence matrix (MCM) and difference between pixels of scan pattern (DBPSP) which describes the texture features and dynamic dominant color (DDC) to extract color feature.

The feature extraction method presented in this paper is a combination of the gradient-based feature with wavelet decomposition. In this section, we review the method of texture analysis by gradient-based feature and the theory of wavelet transform. The formula widely adopted for measuring the e/cacyof a CBIR system is also discussed.

A. **Texture analysis by gradient-based feature**

Features derived from gradient direction images can be used for texture analysis [40-42]. Gradient direction images generated by a gradient operator reflect the magnitude and direction of maximal gray-level change at each pixel of an input image. Such information provides important cues for human visual system. A number of gradient operators such as the popular Sobel operator [44,46] can be used for generating gradient direction images. Assume that there are 360 directions (0◦; 1◦; : : : ; 359◦). By summing up the magnitude value in the same direction at each pixel, a histogram of gradient directions with 360 bins is compiled. Such a histogram can be represented by a vector, called gradient vector, which

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allows us to analyze the texture of an image in terms of its edginess information. To reduce the length of a gradient vector and the sensitivity due to a small change in image's orientation, every successive k directions can be grouped together to form one bin. Therefore, the total number of bins in a histogram of gradient directions will be 360=k. The length of a gradient vector is also 360=k. To measure the difference between two gradient vectors, methods such as Euclidean distance or weighted Euclidean distance can be easily applied.

III. SYSTEM DESIGN AND IMPLEMENTATION STYLE

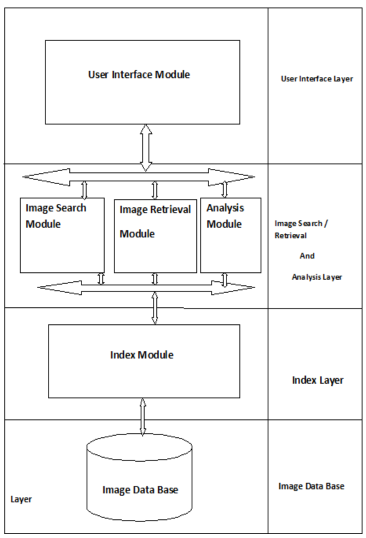

Figure 2 System Architecture

The System is divided into 5 Modules.

A. Data Base Module
B. Index Module
C. Image Search Module
D. Image Retrieval Module
E. Analysis Module
F. User Interface Module

A. Data Base Module: This Module Maintains data base as collection of images.
B. Index Module: This Module used to create Index structure On data base of images.
C. Image Search Module: This Module used to search similar images based on Query Image.
D. Image Retrieval Module: This Module used to retrieve similar images based on Query Image.
E. Analysis Module: This Module compares the performance results on searching the image with index and with out index.
F. User Interface Module: This Module develops user interfaces for various operations.

IV. INDEXING USING KMEANS

The basic aim is to segment colors in an automated fashion using the L*a*b* color space and K-means clustering. The entire process can be summarized in following steps

Step 1: Read the image Read the image from mother source which is in .JPEG format, which is a fused image of part of Bhopal city of Madhya Pradesh, India with DWT fusion algorithm of Cartosat-1 and LISS-IV of Indian satellite IRS-P6 and IRS-1D.

Step 2: For colour separation of an image apply the Decorrelation stretching.

Step 3: Convert Image from RGB Color Space to L*a*b* Color Space How many colors do we see in the image if we ignore variations in brightness? There are three colors: white, blue, and pink. We can easily visually distinguish these colors from one another.

The L*a*b* color space (also known as CIELAB or CIE L*a*b*) enables us to quantify these visual differences.The L*a*b* color space is derived from the CIE XYZ tristimulus values. The L*a*b* space consists of a luminosity layer 'L*', chromaticity-layer 'a*' indicating where color falls along the red-green axis, and chromaticity-layer 'b*' indicating where the color falls along the blue-yellow axis. All of the color information is in the 'a*' and 'b*' layers. We can measure the difference between two colors using the Euclidean distance metric. Convert the image to L*a*b* color space.

Step 4: Classify the Colors in 'a*b*' Space Using K-Means Clustering Clustering is a way to separate groups of objects. K-means clustering treats each object as having a location in space. It finds partitions such that objects within each cluster are as close to each other as possible, and as far from objects in other clusters as possible. K-means clustering requires that you specify the number of clusters to be partitioned and a distance metric to quantify how close two objects are to each other. Since the color information exists in the 'a*b*' space, your objects are pixels with 'a*' and 'b*' values. Use K-means to cluster the objects into three clusters using the Euclidean distance metric.

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Step 5: Label Every Pixel in the Image Using the Results from K-MEANS For every object in our input, K-means returns an index corresponding to a cluster.Label every pixel in the image with its cluster index.
Step 6: Create Images that Segment the Image by Color. Using pixel labels, we have to separate objects in image by color, which will result in five images.
Step 7: Segment the Nuclei into a Separate Image Then programmatically determine the index of the cluster containing the blue objects because Kmeans will not return the same cluster index value every time. We can do this using the cluster center value, which contains the mean 'a*' and 'b*' value for each cluster.

V. IMAGE RETRIEVAL TECHNIQUES

A. **Image Content Descriptors**

Generally speaking, image content may include both visual and semantic content. Visual content can be very general or domain specific. *General visual content* include color, texture, shape, spatial relationship, etc. *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. This chapter concentrates on general visual contents descriptions. Later chapters discuss domain specific and semantic contents. A good visual content descriptor should be invariant to the accidental variance introduced by the imaging process (e.g., the variation of the illuminant of the scene). However, there is a tradeoff between the invariance and the discriminative power of visual features, since a very wide class of invariance loses the ability to discriminate between essential differences. Invariant description has been largely investigated in computer vision (like object recognition), but is relatively new in image retrieval. 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 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. In this section, we will introduce some widely used techniques for extracting color, texture, shape and spatial relationship from images.

B. **COLOR**

Color is the most extensively used visual content for image retrieval [27, 43, 44, 45, 47, 65, 71, 89, 91, 103]. 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.

B.1. **Color Space**

Each pixel of the image can be represented as a point in a 3D color space. Commonly used color space for image retrieval include *RGB*, *Munsell*, *CIE L*a*b**, *CIE L*u*v**, *HSV* (or *HSL*, *HSB*), and *opponent color* space. There is no agreement on which is the best. However, one of the desirable characteristics of an appropriate color space for image retrieval is its *uniformity* . Uniformity means that two color pairs that are equal in similarity distance in a color space are perceived as equal by viewers. In other words, the measured proximity among the colors must be directly related to the psychological similarity among them.

B.2 **Color Moments**

Color moments have been successfully used in many retrieval systems (like *QBIC* [26, 67]), especially when the image contains just the object. The *first order* (*mean*), the *second* (*variance*) and the *third order* (*skewness*) color moments have been proved to be efficient and effective in representing color distributions of images.

B.3. **Color Histogram**

The color histogram serves as an effective representation of the color content of an image if the color pattern is unique compared with the rest of the data set. The color histogram is easy to compute and effective in characterizing both the global and local distribution of colors in an image. In addition, it is robust to translation and rotation about the view axis and changes only slowly

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with the scale, occlusion and viewing angle. Since any pixel in the image can be described by three components in a certain color space (for instance, red, green, and blue components in RGB space, or hue, saturation, and value in HSV space), a *histogram*, i.e., the distribution of the number of pixels for each quantized bin, can be defined for each component. Clearly, the more bins a color histogram contains, the more discrimination power it has. However, a histogram with a large number of bins will not only increase the computational cost, but will also be inappropriate for building efficient indexes for image databases.

B.4. **Color Correlogram**

The *color correlogram* was proposed to characterize not only the color distributions of pixels, but also the spatial correlation of pairs of colors. The first and the second dimension of the three-dimensional histogram are the colors of any pixel pair and the third dimension is their spatial distance. A color correlogram is a table indexed by color pairs, where the *k*-th entry for (*i*, *j*) specifies the probability of finding a pixel of color *j* at a distance *k* from a pixel of color *i* in the image.

C. **Image retrieval by texture similarity**

Our system of image retrieval by texture similarity. Image collection and image retrieval are the two types of major activities that occur in this system. Feature extraction is always required for both image collection and image retrieval. The features extracted from an image are represented by a CSG vector and an EDP-string. Notice that several different images can be mapped to the same EDP-string. Similarly, different images may also be mapped to the same CSG vector. To collect an image, the EDP-string and the CSG vector are stored in the EDPS signature file and the CSGV signature file separately, and the corresponding image is stored in the image database. The relationships among EDP-strings, CSG vectors, and original images are related by the unique image numbers. To retrieve images, we adopt the "query-by-visual-example" method, which is a commonly used approach in CBIR systems, as the man-machine interface. To invoke image retrieval, the user must provide an example texture as the query for the system. Both CSG vector and EDP-string are then extracted from the query image. At the 4rst stage, a search is performed on the EDPS signature file to and the EDP-strings which are matched with the query EDP-string. At the second stage, the image numbers associated with the matched EDP-strings are employed to 4nd all relevant CSG vectors in the CSGV signature 4le and compute their Euclidean distances to the query CSG vector. The original images associated with the first T database CSG vectors, which have the shortest distances between them and the query CSG vector, are retrieved from the database and present to the user.

The algorithm of image retrieval by texture similarity is presented as follows:

Algorithm: Texture image retrieval

Input: A query texture image q and the size of a shortlist T.

Output: A set of database images similar to q.

1. Extract the EDP-string b and CSG vector a from query image q.
2. S ← *b*. For each EDP-string b in the EDPS signature file, add the image numbers associated with b1 to S if EDPS-COMPARISON(b1, bˆ)= "matched".
3. For the image numbers in S, mark their corresponding CSG vectors in the CSGV signature fille.
4. For each marked CSG vector -, compute the Euclidean distance dist(a,a1).
5. Let n be the number of marked CSG vectors and n ∗ = min{T; n}.
6. Find the first n* marked CSG vectors from the CSGV signature file such that their Euclidean distances to a1 is the minimal.
7. Displaythe database images associated with the n* CSG vectors found from the above step in the order of increasing distance to a1.

VI. EXPERIMENTAL RESULTS

The proposed method has been implemented using Java and tested on a general-purpose database containing 1,000 images in JPEG format of size 384x256 and 256x386. The search is usually based on similarity rather than the exact match. We have followed the image retrieval technique, as described in the section 5.1 on different quantization schemes. The quality of the image retrieval, with different quantization schemes has been evaluated by randomly selecting 10 query images, of each category, from the image database. Each query returns the top 10 images from database, and the calculated precision values, using the equation 5, and average precision using equation 8 are given in the Table 1. The average precision (7.8) value of (8, 8, 8) quantization bin indicates the better retrieval results than the others.

The following figure explains Indexing creation process.

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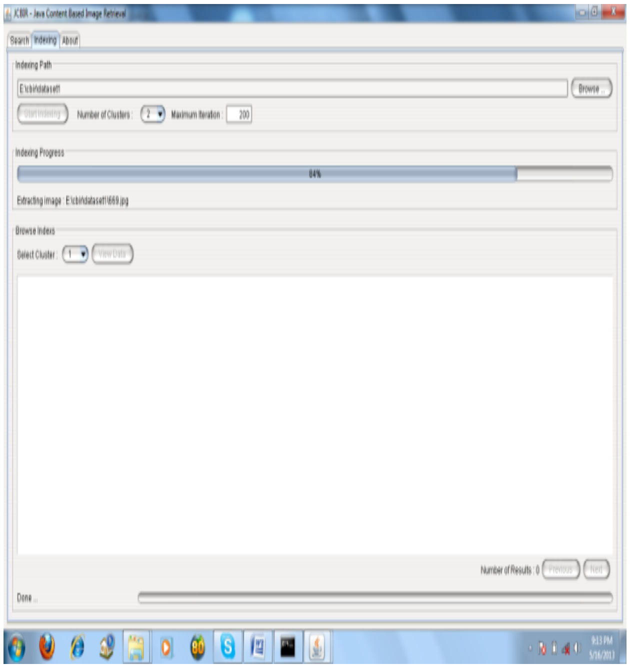

Fig VI.1 Index creation process.

The following figure shows images in index1.

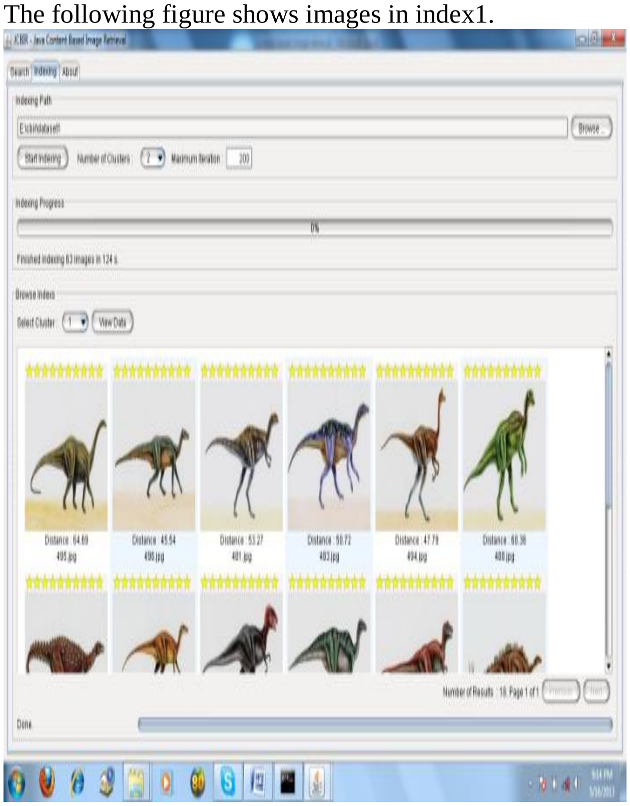

Fig VI.2 Images of Index1.

The following figure shows image search using index.

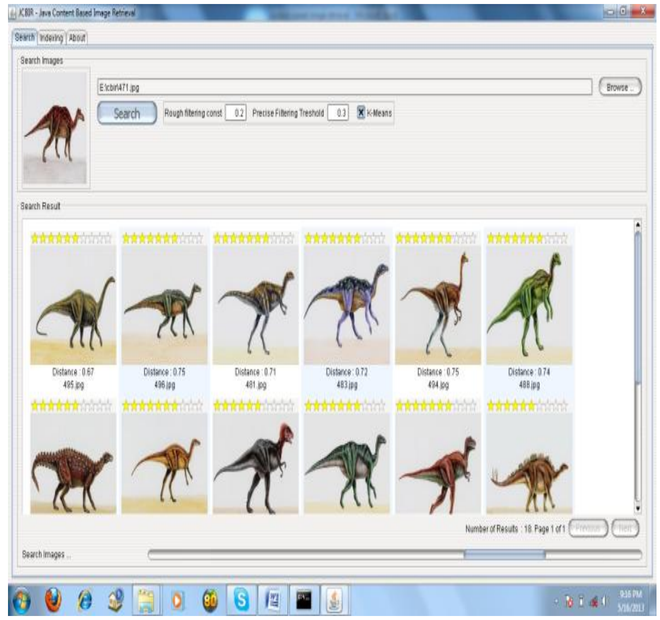

Fig VI.3 Image search using index.

The following figure shows comparison of time complexity between Image search with index and with out index.

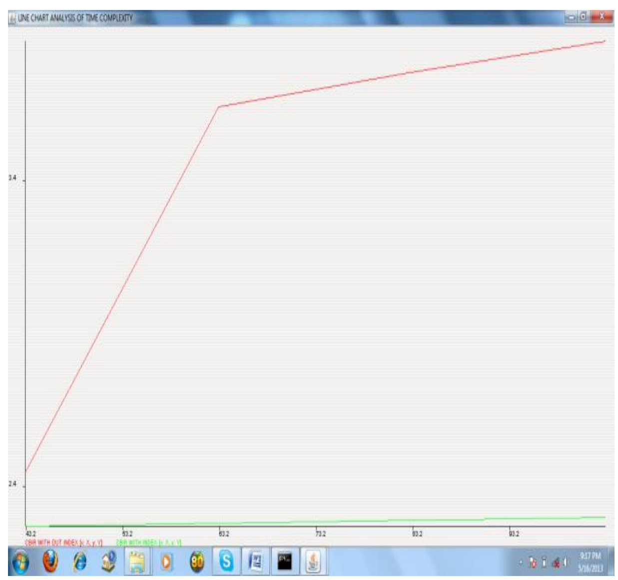

Fig VI.4 Comparison of time complexity.

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The following figure shows comparison of space complexity between Image search with index and with out index.

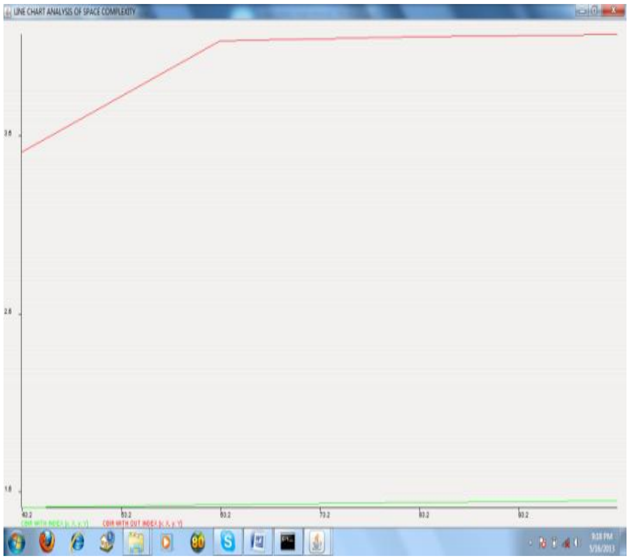

Fig VI.5 Space Complexity between Image search with index and with out index.

The following figure shows comparison of precision complexity between Image search with index and with out index.

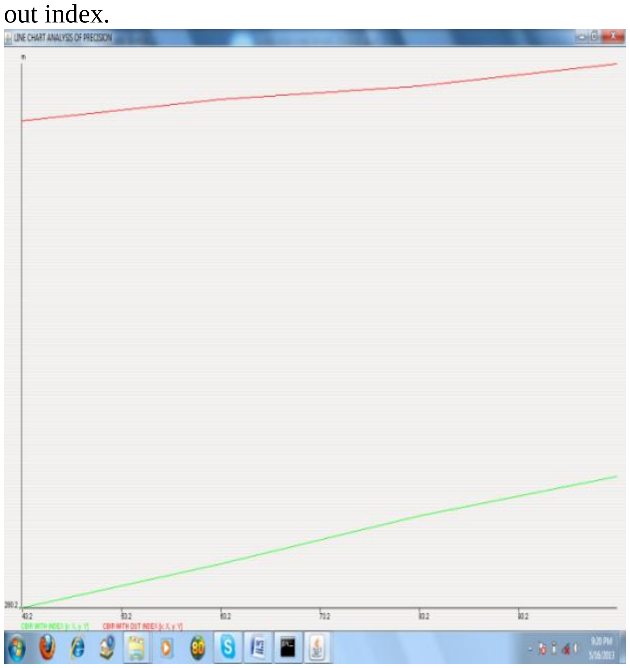

Fig VI.6 Precision Complexity between Image search with index and with out index.

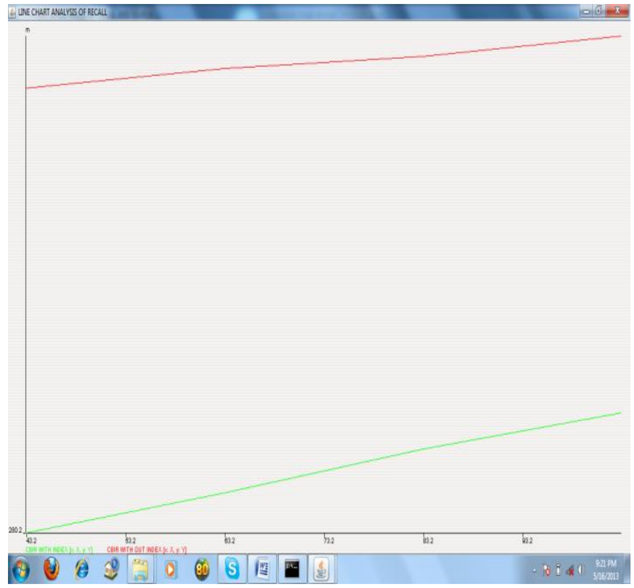

Fig VI.7 recall complexity between Image search with index and with out index.

The following figure shows comparison of time complexity between Image search with index and with out index.

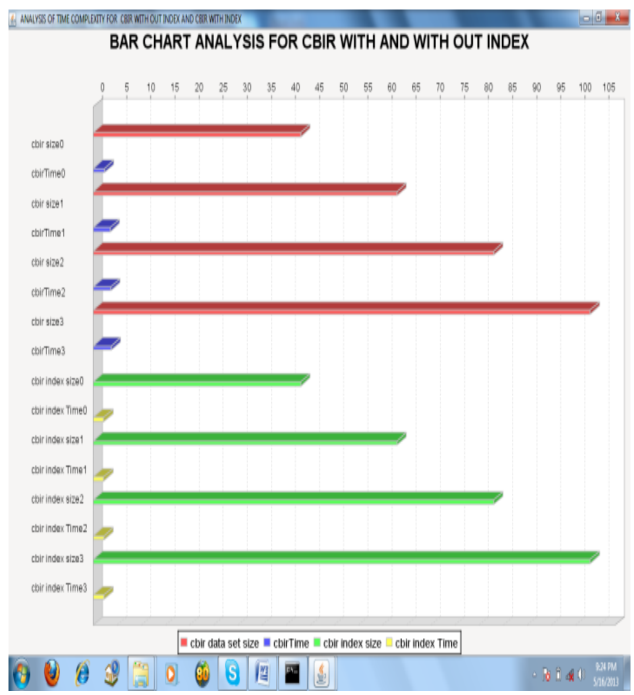

Fig VI.8 Comparison of time complexity.

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The following figure shows comparison of space complexity between Image search with index and with out index.

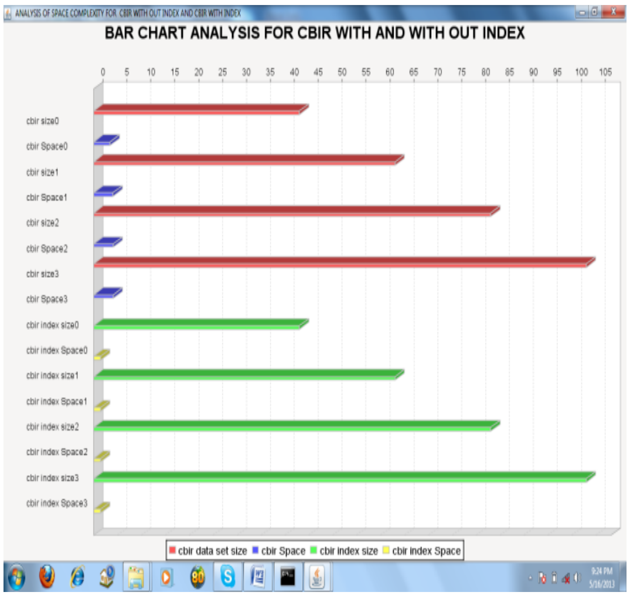

Fig VI.9 Space Complexity between Image search with index and with out index.

The following figure shows comparison of precosion complexity between Image search with index and with out index,

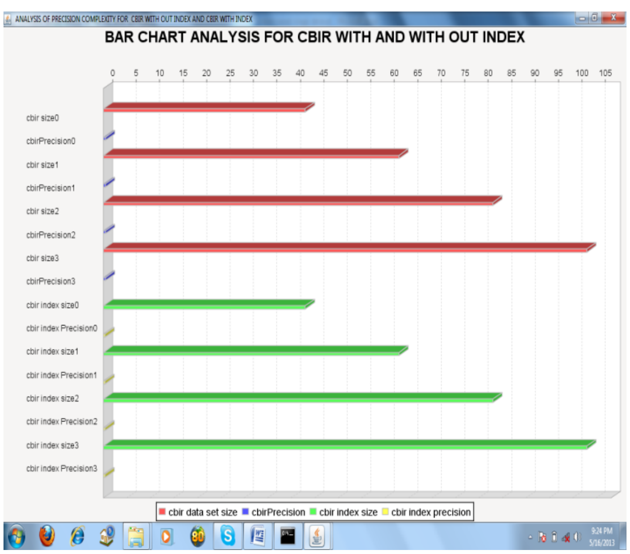

Fig VI.10 Precision Complexity between Image search with index and with out index.

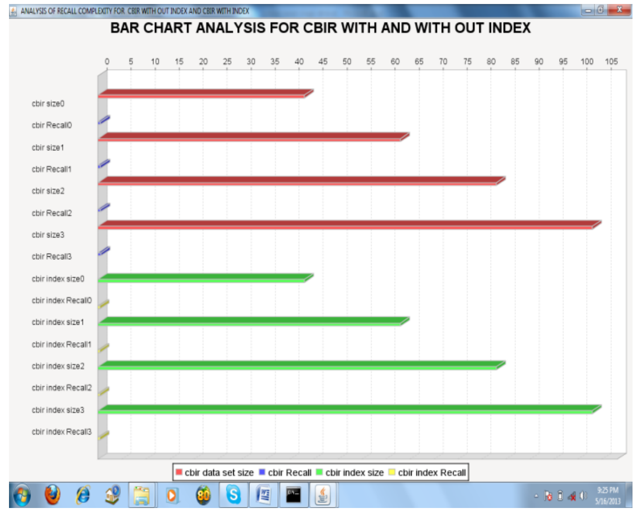

Fig VI.11 recall complexity between Image search with index and with out index.

VII. CONCLUSION

color based image segmentation; it is possible to reduce the computational cost avoiding feature calculation for every pixel in the image. Although the color is not frequently used for image segmentation, it gives a high discriminative power of regions present in the image. This kind of image segmentation may be used for mapping the changes in land use land cover taken over temporal period in general but not in particular.

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