ISSN (Online) 2393-8021
ISSN (Print) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology
Vol. 2, Issue 6, June 2015

Content Based Image Retrieval using Color, Shape and Texture

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Abstract: Image Retrieval system is a novel application for searching and managing large scale image database. Content Based Image Retrieval (CBIR) is a technique which uses visual contents of image such as colour, shape and texture, etc. to search user required image from large scale image database according to user's requests in the form of a query image. Single feature represent only part of the image property so, to enhance the image retrieval effectively we are using multiple features such as colour, shape and texture to represent the whole image property.In this paper we proposed an algorithm which incorporates all three features such as colour, shape and texture to give the advantages of various other algorithms to improve the accuracy and performance of retrieval of images. The accuracy of HSV colour space based colour histogram based matching gives better retrieval result. The speed of shape based retrieval can be enhanced by considering approximate shape rather than the exact shape. Grey Level Co-occurrence matrix (GLCM) is used to extract the texture features of the images. The feature matching procedure is based on the Canberra distance.

Keywords: Content Based Image Retrieval(CBIR), Hue(H), Saturation(S), Value (V), Grey Level Co-Occurrence Matrix (GLCM).

I. INTRODUCTION

With the development of internet and multimedia devices, a huge amount of images has been used in many fields like medical treatment, satellite data, still images repositories, digital forensics and surveillance system. Because of this reason, there is an ongoing demand of systems that can store and retrieve digital images in an effective way. Many digital image storage and retrieval systems have been developed till now for catering these demands. The most common retrieval systems are Text Based Image Retrieval (TBIR) systems, where the search is based on automatic or manual annotation of images. A conventional TBIR searches the database for the similar text surrounding the image as given in the query string. The commonly used TBIR system is Google Images.

However, it is sometimes difficult to express the whole visual content of images in words and TBIR may end up in producing irrelevant results. In addition annotation of images is not always correct and consumes a lot of time.

For finding the alternative way of searching and overcoming the limitations imposed byTBIR systems more intuitive and user friendly content based image retrieval systems (CBIR) were developed. High retrieval efficiency and less computational complexity are the desired characteristics of CBIR systems.

Content-based image retrieval (CBIR) [1] is a technique which uses visual contents such as colour, shape and texture for searching similar images from large scale image database according to user request in the form of query image. Colour, texture and shape features have been used for describing image content.

Content-based image retrieval uses the visual contents of an image such as colour, shape, textureto represent and index the image. In typical content-based image retrieval systems shown in figure1, 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 query image. The system then changes these examples into its internal representation of feature vectors. The similarities /distances between the feature vectors of the query image and those of the images in the database are then calculated and retrieval is performed with the aid of an indexing scheme. The indexing scheme provides an efficient way to search for the image database.

II. RELATED WORK

There are many approaches for Content Based Image Retrieval using different features such as color, shape, and texture. Some of the published work which cover the more important CBIR Systems is discussed below.

Chin-Chin Lai et.al.[2] have proposed an interactive genetic algorithm (IGA) to reduce the gap between the retrieval results and the users' expectation called semantic gap. They have used HSV color space that corresponds to human way of perceiving the colors and separate the luminance component from chrominance ones. They have also used texture features like the entropy based on the grey level co-occurrence matrix and the edge histogram. They compared this method with others approaches and achieved better results

A. Kannan et.al.[3]have proposed Clustering and Image Mining Technique for fast retrieval of Images. The main

ISSN (Online) 2393-8021
ISSN (Print) 2394-1588

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Vol. 2, Issue 6, June 2015

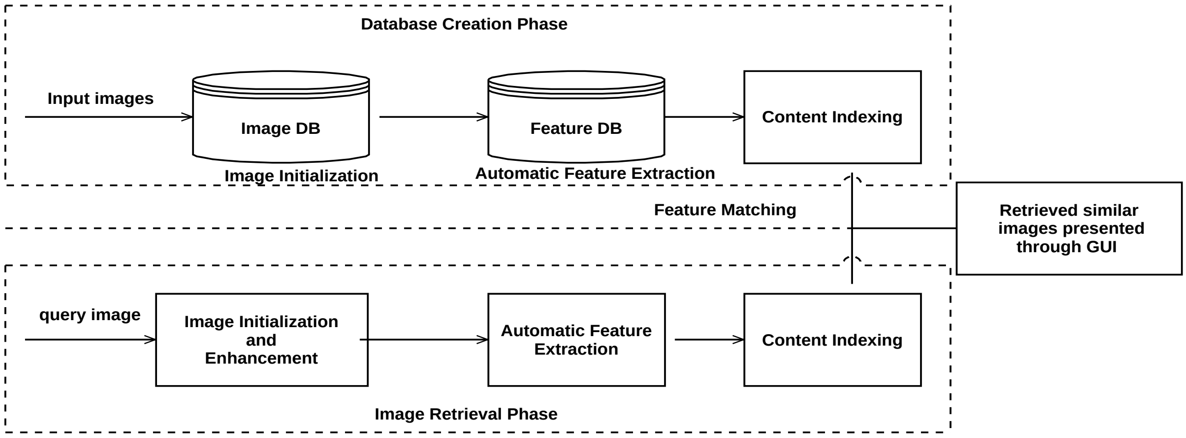

Fig. 1.Content Based Image Retrieval System Framework

objective of the image mining is to remove the data loss and extracting the meaningful information to the human expected needs. The images are clustered based on RGB Components,Texture values and Fuzzy C mean algorithm.

RishavChakravarti et.al [4] have published a paper on Color Histogram Based Image Retrieval. They have used color histogram technique to retrieve the images. This method allows retrieval of images that have been transformed in terms of their size as well as translated through rotations and flips.

A. Ramesh Kumar et.al[5] have published on Content Based Image Retrieval using Color Histogram. They have used Color Histogram technique to retrieve the similar images. To speed up the retrieval, they have used the proposed grid-based indexing to obtain the nearest neighbours of the query image and exact images are retrieved. Indexing can be performed in vector space to improve retrieval speed. Mainly, they have implemented CBIR using color histogram technique and is refined with help of grid technique to improve the image retrieval performance.

III. COLOUR FEATURE EXTRACTION

Color is perhaps the most expressive of all the visual features and has been extensively studied in the image retrieval research during the last decade. Color is a basic visual attribute for both human perception and computer vision [6] and one of the most widely used visual features in image retrieval. The scalable color descriptor (SCD) is defined in the hue-saturation-value (HSV) color space with fixed color space quantization, and uses a novel Haar transform encoding [7].

The HSV color space is a popular choice for manipulating color. The HSV color space is developed to provide an intuitive representation of color and to approximate the way in which humans perceive and manipulate color. RGB to HSV is a nonlinear, but reversible, transformation. The hue (H) represents the dominant spectral component—color in its pure form, as in green, red, or yellow. Adding white to the pure colour changes the color: the less white, the more saturated the colour is. This corresponds to the saturation (S). The value (V) corresponds to the brightness of color. The coordinate system is cylindrical, and is often represented by a subspace defined by a six-sided inverted pyramid. The top of the pyramid corresponds to V=1, with the "white" at the centre. The hue is measured by the angle around the vertical axis, with red corresponding to 0. The saturation ranges from 0 at the centre to 1 on the surface of the pyramid. An inverted cone is also used to denote the subspace instead of the pyramid.

The SCD addresses the interoperability issue by fixing the color space to HSV, with a uniform quantization of the HSV space to 256 bins. The HSV space is uniformly quantized into a total of 256 bins. This includes 4 levels in H, two levels in S, and two levels in V. The histogram values are truncated into a 11-bit integer representation. So it generates the 256 histograms value stored in feature vector database. In similarity matching of histograms, the Canberra distance is used to usually result in good retrieval accuracy. We found, HSV colour space to be better than RGB color space, from literature survey where each component is quantized in non-equal intervals, where H : 16 bins, S : 4 bins and V : 4 bins. Finally, these 16X4X4 bins are concatenated to obtain a 256 dimensional vector [8].

The following steps are followed to extract color feature.

1. Read the query image from user.
2. Convert RGB colour space into HSV color space.
3. Quantize each pixel in HSV space to 256 histogrambins.
4. The normalized histogram is obtained by dividing withthe total number of pixels.
5. Store the 256 values as color feature vector in feature vector database.
6. Calculate the similarity measure of query image and theimage present in the database using Canberra Distance.
7. Retrieve the images based on minimum distance.

ISSN (Online) 2393-8021
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International Advanced Research Journal in Science, Engineering and Technology
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IV. SHAPE FEATURE EXTRACTION

The group of image processing operations which process the image based on shapes is referred as Morphology[9].In morphological operations the output image is created with help of applying structuring element to input image. A morphological operation that is sensitive to specific shapes in the input image can be constructed by choosing the size and shape of the neighbourhood. Dilation and erosion are the most basic morphological operations. Dilation creates the effect of swelling of shapes of the objects by adding pixels to the boundaries of objects in an image, while erosion forms the object shape shrinking effect by removing pixels on object boundaries. The size and shape of structuring element decide number of pixels added or removed from the objects in an image. In the morphological dilation and erosion operations, the state of any given pixel in the output image is determined by applying a rule to the corresponding pixel and its neighbours in the input image.Shapes are often determined by first applying segmentation or edge detection to an image[10]. Other methods use shape filters to identify given shapes of an image [11,12]. In some cases accurate shape detection will require human intervention because methods like segmentation are very difficult to completely automate [13]. Here the paper discusses shape texture extraction using morphological operations like erosion, dilation.

Moment invariants

Hu [15] proposed Moment Invariants (MI) for two-dimensional pattern recognition applications. Two dimensional moments of order $(p+q)$for digital image $f(x,y)$is defined as follows.

m_{pq}=$\sum_x \sum_y x^p\, y^q f(x,y)$ (1)
Where $p,q = 0,1,2$ ....

The summations are over the values of spatial co-ordinates x andy spanning the entire image. The moments in Eq. (1) are not in general invariant under translation, rotation or scale changes in the image f(x,y). Translation invariance can be achieved by using central moment defined as follows.

$$m_{pq} = \sum\sum (x-\bar{x})^p (y-\bar{y})^q\, f(x,y)$$

Where $\bar{x} = \frac{m_{10}}{m_{00}}$ and $\bar{y} = \frac{m_{01}}{m_{00}}$

The normalized central moment of order $(p+q)$ is defined as

$$n_{pq} = \frac{m_{pq}}{{m_{pq}}^{\gamma}}$$

Where $\gamma = \frac{p+q+2}{2}$,

A set of seven 2-D moment invariant that is insensitive to translation, rotation, scaling, mirroring and changing can be derived from these equations. However kernel is not orthogonal [16] redundancy exists in the image representation using these moments.

$M1 = m_{2,0} + m_{0,2}$

$M2$= $\left(m_{2,0} - m_{0,2}\right)^2 + 4{m_{1,1}}^2$

$M3 = \left(m_{3,0} - 3m_{1,2}\right)^2 + \left(m_{0,3} - 3m_{2,1}\right)^2$

$M4 = \left(m_{3,0} + m_{1,2}\right)^2 + \left(m_{0,3} + m_{2,1}\right)^2$

M5=$\left(m_{3,0} - 3m_{1,2}\right)\left(m_{3,0} + m_{1,2}\right)\left[\left(m_{3,0} + m_{1,2}\right)^2 - 3\left(m_{0,3} + m_{2,1}\right)^2\right] + \left(m_{0,3} - 3m_{2,1}\right)\left(m_{0,3} + m_{2,1}\right)\left[\left(m_{0,3} + m_{2,1}\right)^2 - 3\left(m_{3,0} + m_{1,2}\right)^2\right]$

M6= $\left(m_{2,0} + m_{0,2}\right)\left[\left(m_{3,0} - 3m_{1,2}\right)^2 - \left(m_{0,3} + m_{2,1}\right)^2\right] + 4m_{1,1}\left(m_{3,0} + m_{1,2}\right)\left(m_{0,3} + m_{2,1}\right)$

M7=$(3m_{2,1} - m_{0,3})\left(m_{3,0} + 3m_{1,2}\right)[\left(m_{3,0} - m_{1,2}\right)^2 - 3\left(m_{0,3} + m_{2,1}\right)^2]$

The following steps are followed to extract Shape feature.

1. Read the query image from user.
2. Convert RGB query image to Grey Scale image.
3. Calculate 4 morphological gradients of edge maps are generated.
4. Calculate seven moment invariants for each edge map,totally28 features are stored.
5. Compare similarity matching with database image with query image using distance metrics.
6. Retrieve the top ten images based on minimum distance.

V. TEXTURE FEATURE EXTRACTION

Grey Level Co-occurrence Matrix (GLCM) is a widely used texture descriptor and it is proven that results obtained from the co-occurrence matrix are better than the other texture discriminations methods [17]. GLCM computes the statistical features based on grey level intensities of the image.

It enhances the details of image and gives the interpretation. The GLCM is a tabulation of how often different combinations of pixel brightness values (gray levels) occur in an image. The advantage of the co-occurrence matrix calculations is that the co-occurring pairs of pixels can be spatially related in various orientations with reference to distance and angular spatial relationships, as on considering the relationship between two pixels at a time. As a result the combination of grey levels and their positions are exhibited apparently. Therefore it is defined as “A two dimensional histogram of grey levels for pair of pixels, which are separated by a fixed spatial relationship”.

However, the matrix is sensitive to rotation. With the change of different offsets define pixel relationships by varying directions (rotation angle ofan offset$0^0, 45^0, 90^0, 135^0$) and displacement vectors (distance to the neighbour pixel: 1, 2, 3 …), different co-

ISSN (Online) 2393-8021
ISSN (Print) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology
Vol. 2, Issue 6, June 2015

occurrence distributions are resulted from the same image of reference [18].

Construction of the Traditional Co-occurrence Matrix

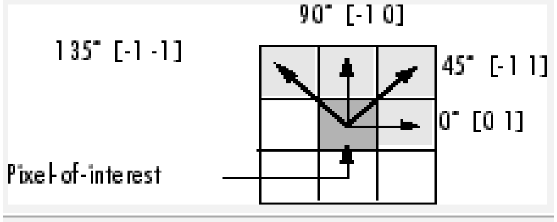

Fig.2. Direction of angle $0^0, 45^0, 90^0, 135^0$for GLCM matrix with distance d=1.

Let I be a given grey scale image. Let N be the total number of grey levels in the image. The Grey Level Co-occurrence Matrix defined by Haralick is asquare matrix G of order N, where the (i, j) the entry of G represents the number of occasions a pixel with intensity i is adjacent to a pixel with intensity j. The normalized co-occurrence matrix is obtained by dividing each element of G by the total number of co-occurrence pairs in G. The adjacency can be defined to take place in each of the four directions (horizontal, vertical, left and right diagonal) as shown in figure 2. The Haralick texture features are calculated for each of these directions of adjacency [10]. The four directions of adjacency for calculating the Haralick texture features. The texture features are calculated by averaging over the four directional co-occurrence matrices. To extend these concepts to n-dimensional Euclidean space, we precisely define grey scale images in n-dimensional space and the above mentioned directions of adjacency in n-dimensional images.

Statistical Features:

From the spatial domain GLCM image being an output of second order statistics, again further statistical parameters like contrast, energy, homogeneity and correlation are determined by applying respective equations as mentioned in the following sections.

$$\boldsymbol{P(i,j|d,\theta)} = \frac{\boldsymbol{P(i,j|d,\theta)}}{\sum_i \sum_j \boldsymbol{P(i,j|d,\theta)}}$$

$$\boldsymbol{Energy} = \sum_i \sum_j \boldsymbol{P(i,j)^2}$$

Energy measures the number of repeated pairs. The energy is expected to be high if the occurrence of repeated pixel pairs is high.

$$\boldsymbol{Homogeneity} = \sum_i \sum_j \frac{\boldsymbol{P(i,j)}}{\boldsymbol{1+|i-j|}}$$

Homogeneity returns a value that measures the closeness of the distribution of element in the GLCM to the GLCM diagonal.

$$\boldsymbol{Contrast} = \sum_{i,j} \boldsymbol{P(i,j)\,|i-j|^2}$$

Contrast measures the local contrast of an image. The contrast is expected to be low if they grey levels of each pixels pair are similar.

$$\boldsymbol{Correlation} = \frac{\boldsymbol{(1-\mu_i)(1-\mu_j)P(i,j)}}{\boldsymbol{\sigma_i\sigma_j}}$$

Correlation provides a correlation between the two pixels in the pixels pair .The correlation is expected to be high if the grey levels of the pixel pairs are highly correlated.

The following steps are followed to extract texture feature.

1. Read the query image from user.
2. Convert RGB query image to Grey Scale image.
3. Compute four GLCM matrices for each direction $0^0, 45^0, 90^0, 130^0$
4. For each GLCM matrix compute the statistical features such as Energy, Homogeneity, Contrast and Correlation.
5. Compare similarity matching of database image with query image using distance metrics.
6. Retrieve the top ten images based on minimum distance.

VI. COMBINING FEATURE

The retrieval result using only single feature may be inefficient. It may either retrieve images not similar to query image or may fail to retrieve images similar to query image. Hence, to produce efficient results, we use combination of color, shape and texture features. The similarity between query and target image is measured from three types of characteristic features which includes color, shape and texture features.So, during similarity measure, appropriate weights are considered to combine the features. The distance between the query image and the image in the database is calculated as follows:

$$d = w1 \times d1 + w2 \times d2 + w3 \times d3$$

VII. SIMILARITY MEASUREMENT

The Canberra distance measure is used for similarity comparison. It allows us the feature set to be in un normalized form. The Canberra distance measure is given by:

$$\textbf{CanbDist}(\boldsymbol{x},\boldsymbol{y}) = \sum_{i=1}^{d} \frac{|x_i - y_i|}{|x_i| + |y_i|}$$

Where x and y are the feature vectors of query and database image respectively, of dimension d.

VIII. PERFORMANCE EVALUATION

The performance of retrieval of the system can be measured in terms of its recall and precision. Recall measures the ability of the system to retrieve all the models that are relevant, while precision measures the ability of the system to retrieve only the models that are relevant. It has been reported that the HSV color space, Morphological invariants and Grey Level Co-occurrence Matrix gives the best performance through recall and precision value [17, 18]. They are defined as

Total

$$Precision = \frac{Number\ of\ relevent\ images\ retrieved}{Total\ number\ of\ images\ retrieved}$$

$$Recall = \frac{Number\ of\ relevent\ images\ retrieved}{Total\ number\ of\ relevent\ images}$$

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International Advanced Research Journal in Science, Engineering and Technology
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IX. EXPERIMENTAL SETUP

The discussed image retrieval methods are implemented using MATLABR2012A,Microsoft Visual Studio on Intel Core i5 processor with 4 GB of RAM. To check the performance of proposed technique a database of 1000 variable sized images spread across 10 categories has been used.

Data set: We used the archaeological images and Wang's [14] dataset consisting of Corel images with ground truth has been used. The image set comprises 100 images in each of 10 categories. The images have a size of 256 x 384 or 384X256. The images with other size are resized to 256X384.

Feature set: The feature set comprises color, shape and texture descriptors computed for each pixel of an image.

X. EXPERIMENTAL RESULTS AND CONCLUSION

All color, shape and texture retrieval algorithms are implemented in MATLAB with the database of 1000 images. All the images are stored in JPEG format with size 384 × 256 or 256 × 384. There are ten different categories.

Fig.3. CBIR output using HSV colorspace Histogram

We have given the query image to CBIR system and we got some images which are related to query image based on the color technique. But the result which has obtained is not satisfactory. So we go for shape retrieval technique.

Fig. 4 CBIR output using shape.

We have given the query image to CBIR system and we got some images which are related to query image based on the Shape technique. But the result which has obtained is not satisfactory. So we go for Texture retrieval technique.

Fig.5. CBIR output using texture.

We have given the query image to CBIR system and we got some images which are related to query image based on the Shape technique. But the result which has obtained is not satisfactory. So we go for Image retrieval using combination of Color, Shape and Texture.

Fig.6. CBIR output using combination of colour, shape and texture.

When we have used the colour, shape and texture features we have got better result.

XI. EVALUATION OF RESULT

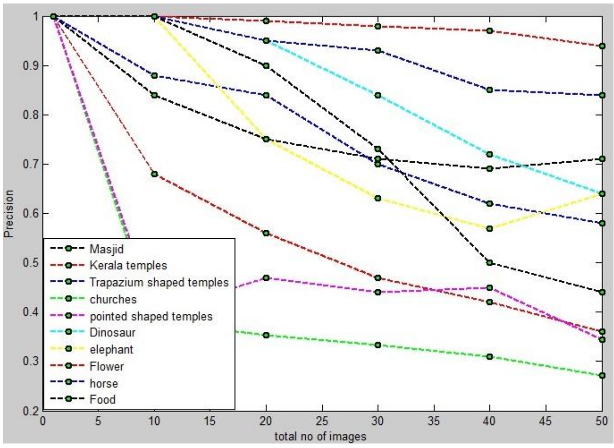

Fig. 7. Graph shows average precision Vs no. Of images

The above graph shows the effectiveness of the image retrieval using color, shape and texture. There are 10 categories of images. X axis represents the no. of images and Y axis represents the average precision. To calculate

DOI 10.17148/IARJSET.2015.2610

average precision we have chosen randomly 5 images from each category and took average precision based on no. of images such as 10,20,30,40 and 50 images.

XII. CONCLUSION AND FUTURE SCOPE

Content based image retrieval has overcome all the limitations of text based image retrieval by considering the visual contents of image such as color, shape and texture. Here we successfully implemented the CBIR system by combining three features i.e., color, shape and texture. In this paper a new algorithm content based image retrieval is presented.(i) HSV color space.(ii)Edge detection and moment invariant.(iii)Grey Level Co-occurrence Matrix(GLCM) are combined to build a feature vector database. Canberra distance are used to match the query image with 10 classes[Masjid, Kerala temples, Trapezium shaped temples,churches,pointed shaped temples,Dinosaur,elephant,Flower,horse,Food] 440 of archaeological monuments images and from 441 to 999 images from WANG image database which uses 1000 images of ten different classes. The proposed method gives better retrieval results and average precision. W e have used only four GLCM statistical features with angle $(0^0, 45^0, 90^0, 130^0)$ and distance d=1.Future work of the study are Grey level Co-occurrence matrices with different angle with different distances and in HSV color space different levels of H,S,V to generate histogram bins.

REFERENCES

[1] RitendraDatta, Dhiraj Joshi, Jia Li and James Wang, "Image Retrieval: Ideas, Influences, and Trends of the New Age", Proceedings of the 7th ACM SIGMM international workshop on Multimedia information retrieval, November 10-11, 2005, Hilton, Singapore.

[2] Chih-Chin Lai, Member, IEEE, and Ying-Chuan Chen," A User-Oriented Image Retrieval System Based on Interactive Genetic Algorithm", IEEE transactions on instrumentation and measurement, vol. 60, no. 10, october 2011

[3] A.Kannan, Dr.V.Mohan, Dr.N.Anbazhagan "Image Clustering and Retrieval using Image Mining Techniques" 2010 IEEE Conference.

[4] RishavaChakravarti, XiannongMeng "A Study Of Color Histogram Based Image Retrieval"2009 Sixth International Conference on Informational Technology.

[5] A.RameshKumar,D.Saravanan "Content Based Image Retrieval Using Color Histogram"(IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 4 (2) , 2013, 242 – 245.

[6] Rui Y, Huang T S, Chang S F. Image retrieval: current techniques,promising directions and open issues, Journalof Visual Communication and Image Representation,1999, 10(I): 39-62.

[7] B. S. Manjunath, Jens-Rainer Ohm, Vinod V. Vasudevan, and Akio Yamada."Color and Texture Descriptors"IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS FOR VIDEO TECHNOLOGY, VOL. 11, NO. 6, JUNE 2001

[8] Smith J R, Chang S F. Tools and techniques for colour image retrieval, in: IST/SPIE-Storage and Retrieval forImage and Video Databases IV, San Jose, CA, 2670, 1996,426-437 .

[9] Dr.H.B.Kekre, SudeepThepade, Priyadarshini Mukherjee, MitiKakaiya, ShobhitWadhwa, Satyajit Singh."Image Retrieval with Shape Features Extracted using Morphological Operators with BTC"International Journal of Computer Applications (0975 – 8887)Volume 12– No.3, November 2010

[10] Sagarmay Deb, Yanchun Zhang, "An Overview of Content Based Image Retrieval Techniques," Technical Report, University of Southern Queensland.

[11] Rafael C. Gonzalez, Richard E. Woods, Digital Image Processing". Chapter 10, pg 599-607.Published by Pearson Education, Inc. 2005.

[12] William I. Grosky, "Image Retrieval - Existing Techniques, Content-Based (CBIR) Systems" Department of Computer and Information Science, University of Michigan-Dearborn, Dearborn, MI, USA,http://encyclopedia.jrank.org/articles/pages/6763/Image-Retrieval.html#ixzz0l30drFVs, referred on 9 March 2010

[13] Bill Green, "Canny Edge Detection Tutorial",2002.http://www.pages.drexel.edu/~weg22/can_tut.html, referred on 9 March 2010

[14] P. S. Hiremath ,JagadeeshPujari. "Content Based Image Retrieval based on Color, Texture and Shape features using Image and its complement"International Journal of Computer Science and Security, Volume (1) : Issue (4).

[15] M.K.Hu, (1962) "Visual pattern recognition by moment invariants", IRE Transactions of Information Theory, 8 (1), pp. 179-187.

[16] L. Yang, and F. Algregtsen, "Fast computation of invariant geometric moments: A new method giving correct results," Proc. IEEE Int. Conf. on Image Processing, 1994.

[17] L. S. Davis, "A survey on edge detection techniques", Comp. Graph. and Image Proc., vol. 4, pp. 248-270, 1975.

[18] GuneetSaini. Texture Analysis of CT scan images. M.Tech.thesis. Electrical and Instrumentation Department, Patiala, India :Thapar University, 2008.

 DOI 10.17148/IARJSET.2015.2610