Advanced Research in Electrical and Electronic Engineering
p-ISSN: 2349-5804; e-ISSN: 2349-5812 Volume 2, Issue 12 July-September (2015) pp. 29-34

http://www.krishisanskriti.org/Publication.html

Content Based Image Retrieval using Texture and Color Feature

Sanjib Kr. Kalita[1] and Bireswar Banik[2]

[1,2]Deptt. of Computer Science Gauhati University
E-mail: [1]sanjib959@rediffmail.com, [2]bireswarbanik02@gmail.com

Abstract— *This paper describes content based image retrieval using texture and color feature of images. For texture feature extraction, GLCM (Gray Level Co-occurrence Matrix) algorithm is used and for color feature the color histogram technique is used. The proposed system has been implemented on WANG database containing 1000 color images of 10 different classes using three different types of distances. Experimental result shows that the retrieval performance is higher in case of Manhattan distance which is around 78.30%.*

Keywords*: Content Based Image Retrieval (CBIR), Texture feature, Color feature, Gray Level Co-occurrence Matrix (GLCM), Distance Formulas etc.*

1. INTODUCTION

An image can derive a complete overview of whole scenery or environment or a complete story. In some interviews like SSB, picture prescription test is taken where from a single image different views of the candidates are come out. This shows how different ideas can come out from a single image. An image retrieval technique is a process which takes an image as input and display similar images. Content Based Image Retrieval is the mostly used technique in present days which have a many advantages over Text Based Image Retrieval. Mainly, it is not possible to use perfect keyword all the time for mentioning exact content of the image.

2. LITERATURE REVIEW

This section describes some limited literature survey on color and texture features for CBIR that we have studied during our study period.

Rui.Y.and Huang. T.S. [1] gives an idea of the survey of image qualities using different methods. They mention the use of CBIR for the real time application and also propose the past and current achievements in indexing and extracting the visual features of an image.Three databases used in the system are i) raw image database, ii) visual feature database that store extracted feature value and iii) text annotation database contains the keywords and descriptor text. It shows an efficient interaction between human and computer where the text based system is integrated with the content based retrieval system.

Ahonen.T describes in [12] content based image retrieval systems for facial recognition and texture classification in image retrieval. A local binary pattern (LBP) operator is used for image retrieval, where the LBP value is found for each pixel in input image and compared with the LBP value of data base images for retrieve images.

Huang.P.W describes in [7] how efficiently similarity of images can measure using texture similarity. They mentioned nicely the advantages of CBIR over text based image retrieval. The texture retrieval is calculated depends on statistical property of the pixel values for grey level images.

C. H. Ling proposes in his paper [4] three image features. i) Texture feature using Color Co-occurrence Matrix (CCM) which calculates the probability of occurrence of same pixel color. ii) Color feature where difference between pixels of scan pattern (DBSP) is used which converts the difference in to the probability of occurrence and color histogram for K-mean (CHKM). iii)CHKM color feature evaluates each pixel of an image and then it is replaced by most common distinct color that is most similar to the color and so as to classify all pixels in an image in to k-cluster. Then, the three features are integrated to develop a new feature called CTCHIRS which works in an efficient way.

3. THEORATICAL BACKGROUND

3.1 Content Based Image Retrieval

"Content-based" means that the searching is performed based on the contents of the image rather than any textual descriptions. The basic three features of CBIR are texture, color and shape.

3.2 Texture Feature

Texture describes the internal properties of the images like surface pattern. Alternatively it describes the properties of all surfaces that represents visual patterns, each having similarity[9].

3.2.1 GLCM

GLCM or Gray Level Co-occurrence Matrix is basically used for texture feature extraction. In 1973, Haralic introduced the co-occurrence matrix and its texture features. GLCM of an image is calculated using a displacement vector d and orientation θ [14]. Let N be the number of Grey Levels of the image, then the GLCM matrix M of size N x N where (i, j) th entry of the matrix is represented by number of times of a pixel with intensity i is adjacent to intensity of j[14].

$$Mi,j = M(i,j) = \sum_{x=1}^{N}\sum_{y=1}^{N} \begin{cases} 1, if\ I(x,y) = i\ and \\ I(x+\Delta x, y+\Delta y) = j; \\ 0, otherwise \end{cases} \quad (1)$$

Where (Δx, Δy) is the offset based on the given angle θ and distance d, which shows the distance between a pixel and its neighbor. The θ has 8 different angular values such as 0°,45°,90°,135°,180°,225°,270°,315°.If the symmetric property of GLCM is set to true, it counts the adjacent values irrespective of order i.e. the value of (0° and 180°), (45° and 225°), etc are same.

Considering a 4 x 4 grey level image as depicted in*Fig. 1* and calculates the symmetric GLCM matrix forθ = 0° and d=1,where offset is [1 0] or [0 1] using *equation 1*;That means it counts the number of occurrences of intensity i with j horizontally.

Fig. 1 shows that the value 3 and 4 occurs two times: one is (3,4) and other is (4,3). So, the value of $M_{3,4}$ and $M_{4,3}$ is 2. If the property is set to false then the both value becomes 1. The Normalization of GLCM matrix is performed by dividing each element by sum of all elements i.e. 23 so that the sum of all elements of Normalized GLCM becomes 1 [22].

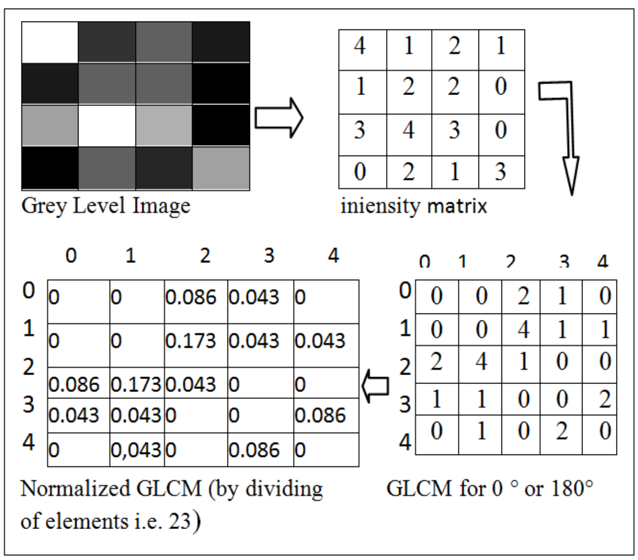


Fig. 1: GLCM matrix evaluation

The following properties of GLCM are calculated for retrieving texture values [16, 22]:

Contrast: It measure of the intensity or gray level variations between a pixel and its neighbors.

$$\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(i-j)^2 P(i,j) \quad (2)$$

Where P(i, j)= (i,j)th entry of the Normalized GLCM P.

Correlation: It is themeasure of correlated pixels to their neighbors in the matrix.

$$\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\frac{(1-\mu_x)(1-\mu_y)P(i,j)}{\sigma_x\sigma_y} \quad (3)$$

Where μ_x, μ_y, σ_x, $\sigma_y$are the mean and standard deviations of P_x and $P_{y.}$ calculated as equation (3.1) to (3.3) which are equal for symmetric GLCM.

$$\mu_x = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} i.P(i,j)\ and$$

$$\mu_y = \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} j.P(i,j) \quad (3.1)$$

$$\sigma_x = \sqrt{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(i-\mu)^2 P(i,j)} \text{ and}$$

$$\sigma_y = \sqrt{\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}(j-\mu)^2 P(i,j)} \quad (3.2)$$

$$P_x = \sum_{j=0}^{N-1} P(i,j) \text{ and } P_{y=} \sum_{i=0}^{N-1} P(i,j) \quad (3.3)$$

Energy: It is the measure of the sum of squared elements in the GLCM.

$$\sum_{i=0}^{N-1}\sum_{j=0}^{N-1} P(i,j)^2 \quad (4)$$

Homogeneity: It measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

$$\sum_{i-0}^{N-1}\sum_{j=0}^{N-1}\frac{P(i,j)}{i+(i-j)} \quad (5)$$

3.3 Color Feature

Image color is also an important feature and takes a big role in retrieval process. In this paper, we convert the image from RGB color model to HSV color model.

3.3.1 Conversion of RGB TO HSV

Conversion of an image from RGB color model to HSV color model [24, 2] is performed as in equation (6) to (8).

$$\text{Hue (H)} = \cos^{-1}\frac{0.5[(R-G)+(R-B)]}{\sqrt{(R-G)^2+(R-B)(G-B)}} \quad (6)$$

$$\text{Saturation (S)} = 1 - \frac{3[MIN(R,G,B)]}{R+G+B} \quad (7)$$

$$\text{Value (V)} = \frac{R+G+B}{3} \quad (8)$$

The normalized hue value varies between from 0 to1, where 0 being red. The range of Saturation is from 0 to 1, where lower the saturation value, the more gray is present. Values are also from 0 to 1, where 0 being totally dark and 1 is bright [11, 16].

3.3.2Color Histogram techniques

It is a type of bar graph where the height of each bar represents the amount of a distinct color in the image. The color histogram values are extracted in two ways [8, 20]. First, GCH (Global Color Histogram) is used for finding the amount of a particular color in the image. The second way is LCH (Local Color Histogram). It is similar as GCH but first it divides the image into fixed number of segments and evaluatescolor histogram values for each segment individually. In this paper, 8 color histogram values are evaluated from HSV color model image viz. gives red, green, blue, yellow, cyan and magenta where with black and white.

3.4 Similarity Measures

The similarity of images is measured by calculating the distance between the feature vectors of query image and stored database images. The images which have less distances will be considered as more similar images.In this work, for similarity measures three distances are used [13], [2]. Let the query feature vector as Q and the database feature vector as d.

Euclidean Distance: It evaluates the square root ofthe squared sum of absolute differences between two vectors.

$$D=\sqrt{\sum_{i=1}^{n}(|Q_i| - |d_i|)^2} \tag{9}$$

Where i=1, 2 , 3, ….n are numbers of features.

Manhattan Distance: It is also known as City block distance. It is calculated by finding the sum of absolute difference of two feature vectors of the images.

$$D=\sum_{i=1}^{n}(|Q_i - d_i|) \tag{10}$$

Chessboard Distance: This distance is used to get the largest value of absolute difference between feature pair.

$$D=\max\{|Q_1 - d_1|, |Q_2 - d_2|, \ldots |Q_n - d_n|\} \tag{11}$$

3.5 PerformanceEvaluation

The Performance of the experiment is evaluated using. Precision and Recall are used as equation (12) and (13). These are defined as [18, 13]:

PRECISION: It is defined as the ratio of retrieved similar (relevant) images to the total number of images retrieved.

$$\text{Precision}=\frac{Numbersofsimilarretrievedimages}{Totalnumberofretrievedimage}=\frac{X}{X+Y} \tag{12}$$

RECALL: It is defined as the ratio of the number of relevant images to the total number of relevant images in the database.

$$\text{Recall}=\frac{Numbersofsimilarretrievedimages}{Totalnumberofsimilarimagesinthedatabase}=\frac{X}{X+Z} \tag{13}$$

4. EXPERIMENTAL SET UP

4.1 Methodology

The aim is to retrieve images from a stored database depending on the query image. The present study is based on the following stepsdepicted in Fig. 2[9, 10].

Step 1: Collection of Images
- Images are stored in database in JPG format

Step 2: Texture feature extraction
- Convert RGB to Grey level image.
- Find GLCM matrix value of the image.
- Calculate the 4 texture features
- Feature vectors are stored in2D array

Step 3: Color feature extraction
- Partition the images in 4 segments (For LCH only)
- Convert RGB value to HSV of the image.
- Calculate eight color histogram values of image.
- Color values are stored in 2D array.

Step 4: Input the query image
- Take the input of the query image.
- Step 2 & 3 is performed for the image.

Step 5: Similarity measures
- Calculate the sum of distance between texture value and color value (LCH) for combined Color and Texture feature.
- Similarity is measured between two feature vectors using 3 different distance formulas.

Step 6: Retrieval of Images
- Compare and Retrieve all the images with least distance based on number of query image.

Fig. 2: Steps are performed for Image Retrieval

4.2 Feature Extraction

In the present study, for extracting features of images a standard database known as Wang Database from [21]

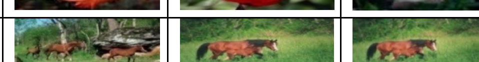
Class Name	Images
African People	
Seas	
Monuments	
Buses	
Dinosaurs	
Elephants	
Roses	
Horses	
Mountains	
Food	

Fig. 3: 3 random images of 10 classes of WANG database

is considered which consists of 1000 images as a total of 10 different classes consist of 100 images in each. Each image has size either 386 * 256 or 256 *386 pixels. Fig. 3 shows 3 random images of each ten class of the experimental database.

The feature extractions of images are shown by taking example of an image of Food class (the highlighted image of Food class in Fig. 3). For texture feature extraction, the image is converted to grey level image by taking number of grey level as 8.The symmetric GLCM matrix of 8x8 dimension is calculated for 0° or 180° by taking offset as [0 1] or [1 0] using equation (1).

Fig. **4** depicts the GLCM matrix for an image of food class. The calculated GLCM matrix is the normalized by dividing all the elements by sum of all elements. Table 1 depicts the texture features calculated using equation (2-5) of The Normalized GLCM.

$$\begin{pmatrix} 2349 & 1293 & 233 & 96 & 46 & 23 & 1 & 0 \\ 1377 & 19565 & 3624 & 699 & 305 & 158 & 42 & 3 \\ 200 & 3698 & 27476 & 1590 & 578 & 268 & 135 & 8 \\ 74 & 646 & 1807 & 3872 & 1541 & 469 & 277 & 19 \\ 25 & 239 & 528 & 1851 & 4864 & 1344 & 441 & 50 \\ 23 & 106 & 222 & 422 & 1596 & 4856 & 1337 & 64 \\ 2 & 32 & 98 & 215 & 429 & 1463 & 4939 & 153 \\ 0 & 2 & 4 & 17 & 28 & 55 & 191 & 9 \end{pmatrix}$$

Fig. 4: GLCM matrix of the Food Class image

Table 1: 4features extracted from Normalized GLCM

Property	**Contrast**	**Correlation**	**Energy**	**Homogeneity**
Value	0.7223	0.8663	0.1334	0.8314

For color feature extraction using GCH, the whole image is converted to HSV using equation (6-8) and 8 color histogram values are extracted. For LCH method, the images are partitioned into four segments and as a total of 32 color values for a single image are extracted as in Table 2. This process continues for all the images and as total of 32 * 1000=32000 histogram color values are stored in the 2D array of LCH color feature.

Table 2: Histogram Color Values evaluated using LCH of a food class image

Partiion no.	**Red**	**Green**	**Blue**	**Yellow**	**Cyan**	**Magenta**	**Black**	**White**
1	0.0458	0.0028	0	0.0195	0	0	0.0034	0
2	0.0497	0.0034	0.0001	0.0279	0.0001	0.0004	0.0043	0.0012
3	0.0824	0.0043	0.0008	0.0573	0.0002	0.0004	0.0049	0.0008
4	0.0770	0.0093	0.0013	0.0639	0.0144	0.0012	0.0057	0.0014

5. RESULT AND DISCUSSION

The experiment is performed by taking 10 images of each class as input query images.

Table 3: Precision value for four different features with L=5, 10, 20,40,60,80,100 (using Euclidean distance)

Feature Name	**Number of Retrieved images**						
	5	**10**	**20**	**40**	**60**	**80**	**100**
Texture Feature	61.00	**54.10**	50.55	45.30	42.88	40.23	38.19
Color (GCH)	67.40	**57.40**	50.75	44.00	39.85	36.45	34.05
Color (LCH)	69.80	**60.00**	52.30	45.62	40.50	37.74	35.31
Color(LCH)+texture	82.20	**74.20**	65.75	57.00	51.73	47.70	44.33

The precision value (in %) for texture feature, color feature for whole image (GCH), color feature by partitioning the image (LCH) and for combine texture and color feature (LCH) is evaluated in Table 3 *using* Euclidean Distance for different number of images retrieved (**L**). For combined feature of color (LCH) and texture. It is clearly observed that a retrieval using combined color (LCH) and texture feature together perform better than other features. So, for further experiment the performance for only combined color and texture featureare considered.

Table 4 depicts the average precision using equation (12) of each10 classes using Euclidean distance for combined feature of color (LCH) and texture. The precision value of Dinosaur class is highest.

Table 4: Precision value for ten classes using color (LCH) and texture feature (using Euclidean distance)

Class Name	**Number of retrieved images**						
	5	**10**	**20**	**40**	**60**	**80**	**100**
African People	74.00	72.00	61.00	50.25	44.00	39.00	35.40
Seas	74.00	58.00	43.00	39.00	33.50	30.87	29.60
Monuments	72.00	55.00	47.00	38.50	33.50	31.00	28.20
Buses	98.00	93.00	78.50	67.25	59.16	51.25	47.10
Dinosaurs	100.00	100.0	100.0	100.0	100.0	99.12	95.50
Elephants	64.00	57.00	49.00	39.75	35.66	32.50	29.30
Roses	96.00	95.00	92.00	88.50	84.83	80.37	75.80
Horses	90.00	80.00	70.00	53.25	47.66	42.50	37.90
Mountains	66.00	53.00	42.00	31.25	28.00	25.75	24.10
Food	88.00	79.00	75.00	62.25	51.00	44.62	40.50
Average	82.20	74.20	65.75	57.00	51.73	47.70	44.33

Average Precision of Combine feature of Color (LCH) and texture retrieval of Euclidean distance is compared with Manhattan Distance and Chessboard Distance which shows that Manhattan distance gives the better result which is depicted in Table 5.

Table 5: Average Precision Value (in %) for different number of retrieved image using 3 distances

Type of distances	**Number of images retrieve**						
	5	**10**	**20**	**40**	**60**	**80**	**100**
Euclidean Dist	82.20	74.20	65.75	57.00	51.73	47.70	44.33
Manhattan Dist	83.20	78.30	71.60	63.52	58.03	53.81	49.4
Chessboard Dist	79.40	70.60	59.30	51.40	46.75	43.0	39.92

The Recall value (in %) of each class taking 10 input images from each class is calculated using equation (13) as depicted in Table 4.

Table 6: Recall Value (in %) of 10 classes using 3 distances

Class Name	Euclidean distance	Manhattan distance	Chessboard distance
African People	35.40	40.20	29.80
Seas	29.60	32.80	27.00
Monuments	28.20	35.00	24.70
Buses	47.10	52.60	42.90
Dinosaurs	95.40	95.50	93.60
Elephants	29.30	33.10	26.40
Roses	75.80	75.30	72.00
Horses	37.90	49.80	31.00
Mountains	24.10	30.20	19.90
Food	40.50	49.70	31.00
Average	44.33	49.42	39.92

5.1 Comparisons with other methods

The average precision value for Combine feature of color (LCH) and texture feature using Euclidean distance and Manhattan Distance for 10 numbers of images of each class is compared with 4 of the standard papers result which clearly shows a better effectiveness and efficiency in image retrieval.

Table 7: Comparison of precision values in our method with other four standard reports

Classes	Our Method1 **(Euclidean Dist)**	*Our Method 2* ***(Manhattan Dist)***	**Manimala [18]**	**CH Ling [4]**	**Huang Dai [7]**	**Jnwhr Et all [19]**
People	**72.00**	71.00	65.00	68.30	42.40	45.25
Seas	58.00	58.00	**62.00**	54.00	44.55	39.75
Monuments	55.00	66.00	**71.00**	50.15	41.05	37.35
Buses	93.00	**94.00**	92.00	88.80	85.15	74.10
Dinosaur	**100.0**	**100.00**	97.00	99.25	58.65	91.45
Elephants	57.00	61.00	**86.00**	**65.80**	42.55	30.40
Roses	**95.00**	**95.00**	76.00	89.10	89.75	85.15
Horses	80.00	**94.00**	87.00	80.25	58.90	56.80
Mountains	53.00	**58.00**	49.00	52.15	26.80	29.25
Food	79.00	**86.00**	77.00	73.25	42.65	36.95
Average	**74.20**	**78.30**	**76.20**	**72.70**	**53.24**	**52.64**

The paper of M.singha et al. [18]compare its wavelet transform for texture feature and wavelet based color histogram method for color retrieval by taking 10 input images of each class of WANG database where each query retrieves top 10 similar images of the database. Another paper by C.H. Ling [4] used a new method which is definitely a significant one [4] for 10 numberof retrieved images. This paper compared with two basic standard paper for CBIR, viz. [7],[19] which are also used for comparisons. Compare to them our present method for both distances shows a better result for Manhattan Distance as depicted in Table 7.

The graphical representations in Fig. 4, Fig. 5 and Fig. 6 summarize the whole performance of the retrieval system. Fig. 4 clearly shows that the retrieval using combined texture and color feature is much better than individual features. Fig. 5 depicts the performance of Manhattan distance which is higher than other two distances. The performance of Manhattan distance and Euclidean is compared with four other papers in Table 7. Fig. 6 shows the average precision values of our method which is comparatively higher than other.

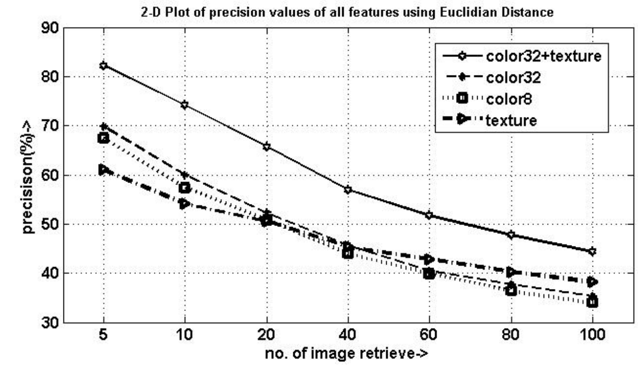


Fig. 4: 2-D plot of Precision value for four features using Euclidean distance (Graphical Representation of Table 3)

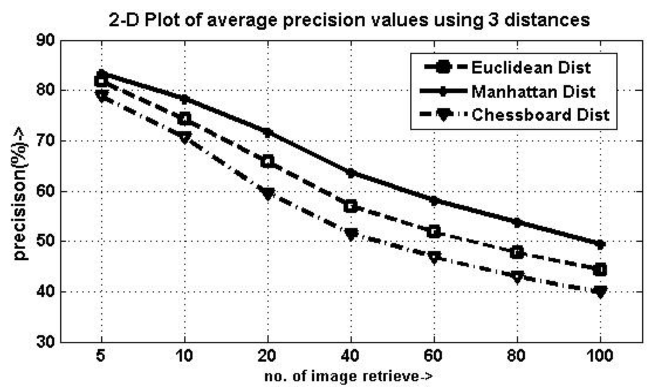


Fig. 5: 2-D plot of average precision (%) values for 3distances (Graphical Representation of Table 5)

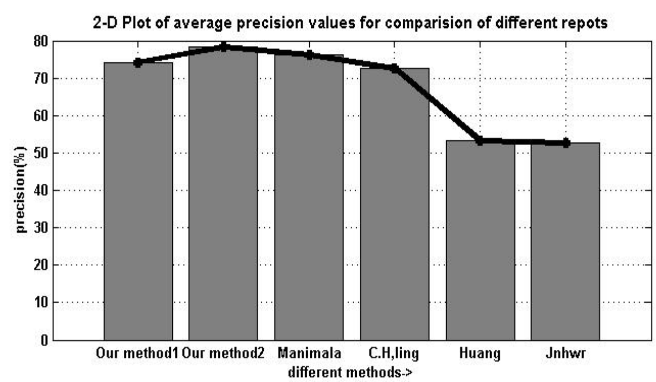


Fig. 6:2-D plot of comparisons of average precision values of Different Methods (From Table 7)

6. CONCLUSION

The proposed system has extracted combine feature of texture and color where texture features are extracted by GLCM algorithm and color features are extracted by finding color histogram values in HSV format. For similarity measures and retrieving images three distances namely Euclidean distance, Manhattan distance and Chessboard distance are used. From this both Euclidean and Manhattan distance shows efficient result comparing with other four standard papers.

As **future work**, the experiment could be performed with some other features like shape.Moreover, it could be used for some other classifiers line SVM, Neural network etc.

REFERENCE

[1] Rui. Y. and Huang T. S.,"Image Retrieval current techniques, promising directions and open issues", Journal of Visual Communication Image Representation, vol-10 no. 1. pp 39-62 March 1999.

[2] Arthi K. and VijayaraghavanJ,"Content Based Image Retrieval Algorithm Using Color Models", IJARCCE, vol-2, issue 3, March 2013.

[3] Sulochana. S. andVidya. R.,"Texture Based Image Retrieval Using Framelet Transform and GLCM", International Journal of Advanced Research in Artificial Intelligence, Vol 2, No 2, 2013.

[4] Lin.,C.,H., Chen,R.T., Chan,Y.K.,"A Smart Content Based Image Retrieval System Based on color and Texture Feature ", Image and Vision Computing, Vol-27,pp- 658-665, 2009.

[5] Rao,M.B., Rao,B.P., and Govardhan, A., "CTDCIRS: Content based Image Retrieval System based on Dominant Color and Texture Features", International Journal of Computer Applications, vol. 18–No.6, 2011.

[6] Mehta. R., Mishra. N, Sharma. S.," Content Based Image retrieval System ", International Journal of Computer Application, vol-24, no-5, June2011.

[7] Huang, P.W., Dai, S.K., "Image retrieval by texture similarity, Pattern Recognition", pp 665–679, 2003.

[8] Shriram KV, PLK Priyadarsini, "An efficient and generalised approach for CBIR in Matlab",I.J image, Graphics and Signal Processing, vol-12,pp 42-48,2012.

[9] Sakhare,S.V., Nasre, V.G.,"Design of Texture Extraction in CBIR using Color and Texture ",www.interscience.in.

[10] Dange, A., Khede, M., "Performance Evaluation of different techniques for texture classification", Department of Electrical Engineering, VIT, Pune.

[11] Singh, S.M., Hemachandran, K**., "**Content Based Image Retrieval using Color Moment and Gabor Texture Feature", International Journal of Computer Science Issues,vol-9, issue 5, No1,September2012

[12] Ahonen, T., Hadid, A., and M. Pietikainen, "Face description with local binary patterns Applications to face recognition," IEEE Trans.Pattern Anal. Mach. Intell., vol. 28, no.12, pp. 2037–2041, Dec.2006.

[13] Malik. F ,Baharudin. B., "Analysis of distance metrics in content-based image Retrieval using statistical quantized histogram texture features in the DCT domain", Journal of King Saud University Computer and Information Sciences (2013) 25,207 –218, www.sciencedirect.com.

[14] Eleyan. A., Demirel. H., "Co-occurrence matrix and its statistical features as a new approach for face recognition", Turk J Elec. Eng& Comp Science ,vol.19, no.1, 2011.

[15] CBIR,http://en.wikipedia.org/wiki/Contentbased_image_ retrieval.

[16] www.mathworks.in, matlabHelp Demos.

[17] RGB color model, http:// en.wikipedia.org / wiki/C content based image retrieval.

[18] Singha, M., Hemachandran. K, "Content Based Image Retrieval using Color and Texture", Signal & Image Processing : An International Journal (SIPIJ) vol -3, no-1, February 2012.

[19] Jhanwar, N., Chaudhurib, S., Seetharamanc, G., Zavidovique, B., "Content based image retrieval using motif coccurrence matrix", Image and Vision Computing,vol-22,pp- 1211–1220, 2004.

[20] http://tarekmamdouh.hubpages.com/hub/Global-and Local-Color-Histogram.

[21] http://wng.ist.psu.edu/docs/related.

[22] Gadkari. D.,"Image Quality Analysis Using GLCM",B.S.E.E University of Pune,2000.