RESEARCH ARTICLE OPEN ACCESS

Retrieval of Images Using Cascaded Features

N. Puviarasan*, Dr. R. Bhavani **
*(Associate Professor, Department of CSE, Annamalai University, Annamalainagar)
** (Professor, Department of CSE, Annamalai University, Annamalainagar)

ABSTRACT
Color and texture are important features of an image. Content-based image retrieval (CBIR) is a process to retrieve similar images for a given query image from large image database. It is proposed to extract the features using cascading method. In this paper, color features are extracted using the first order statistical features like mean, standard deviation, energy, entropy, skewness and kurtosis of an image. After color feature extraction, similarity measurement between query image and database images is done using city block distance (CBD), Canberra distance (CD) and Minkowski distance (MD). The minimum distance top ranked 150 relevant images are retrieved. Then, the five Haralick texture features are extracted only from this 150 images. Again, the same similarity measurements are done. Top ranked relevant images are retrieved. In this study, the comparative work of similarity measurements is also done. It is found that the Canberra distance gives better results to retrieve the similar images.
Keywords - Color features, Haralick features, Canberra distance, Minkowski distance, City block distance

I. INTRODUCTION

The image retrieval system is to retrieve set of images from the image database such that the required images are retrieved. Image retrieval system is divided into two types i) Text based image retrieval ii) Content based image retrieval. In early days the first was familiar. But, it is tedious because of specifying manual annotations for each image. So, it is slow and time-consuming process.

This problem is resolved using content-based mage retrieval(CBIR). In CBIR there are two phases. i) Feature extraction: Extracting features called image signatures which identify the unique nature of images using efficient methods ii) Similarity measurement : Similarity measurement between query images and images in the database is done using distance metrics. Then, the closest distance images are retrieved as the most relevant images.

The first CBIR was QBIC [1]. A number of general purposes CBIR have been developed since then. They used different algorithms for their softwares. PhotoBook [2], Virage [3], Visualseek [4], Netra [5] and SIMPLIcity [6]. In [7] the features are extracted using discrete cosine transform (DCT), fast fourier transform (FFT). The similarity measurement is found using Euclidean distance. It is mentioned that FFT outperforms DCT. In [8], DCT features and HSV color features are extracted. It is found that the CBIR gives 70.07% of accuracy. In [9], the features are extracted using DCT and DCT wavelet. The sector size of 4,8,12 and 16 are used. For similarity measurement, the Sum of absolute difference and Euclidean distance are used. In this paper[10], three color features like color histogram, color coherence vector and color moments are taken. Similarity measurement is done using neural network method. This paper[11], used 2D dual tree discrete wavelet transform as feature vector. Fast Fourier Transform (FFT) and Hue and saturation component of image of HSI color space are used as feature vectors in [12]. This paper [13] use Golomb-Rice coding, which codes the floating point of the color histogram values and XOR bitwise operation is used for similarity matching.

In this paper [14], combing method for distance histogram and moment invariants are used as feature vector. This paper [15] uses color average mean technique for retrieval of images. Feature extraction based on central tendency is proposed. In [16], sectorization of DST transformed components is used as feature vector. In this work addition of the mean of zero and highest row components and mean of zero and highest column components of column transformed values are used
as feature vector.

In [17], contourlet transform features are used to extract similar images from image database. They also used combination of laplacian pyramid and Directional Filter Bank (DFB) as feature vector and found that contourlet transform gives better results. Color and texture features are extracted using Walsh wavelet. Prewitt, Canny and Sobel operators used to extract shape features in [18].

In [19], Color moments are used for color features and Gray level co-occurrence matrix (GLCM) is used for texture features.

It is found that in the above literature, cascaded features of first order statistical properties and Haralick features are not considered. It is very important to find the most similar images. To extract maximum number of similar images, it is proposed to perform cascading operations.

II. PROPOSED WORK

In this research work, after removal of noise from the image, the first order statistical features of image which signify the color features are extracted. Similarity measurement between query image and database images are done using City block distance (CBD), Canberra distance (CD) and Minkowski distance (MD). The minimum distance top ranked 150 images are retrieved. Next, the Haralick features are extracted from 150 images only and it reduces the computational time. Again, the same similarity measurements are used to retrieve more similar images

1.1 Preprocessing

The block diagram of proposed CBIR system is shown in Figure 1.

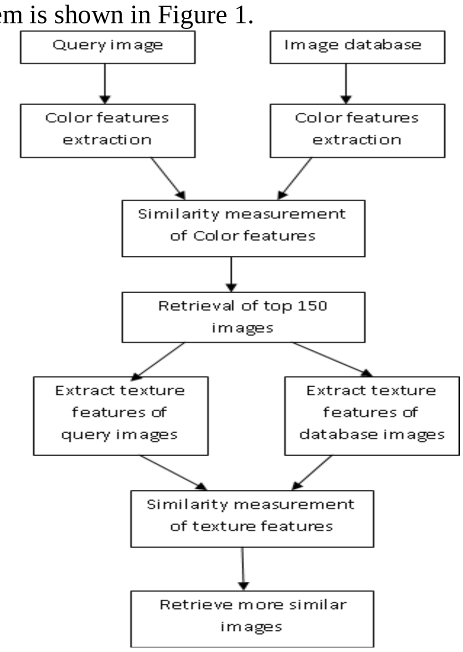

Figure 1: Block diagram of proposed CBIR Method

In the process of noise removal, the median filtering is used to remove the noise. By median filtering, the value of an output pixel is determined by the median of the neighborhood pixels.

III. METHODS AND MATERIALS

3.1 The statistics of images

Images in the database have definite statistics. Such images fit a description of randomly generated pixels. The different features of images are described by the n^{th} order statistics. For example, the first order statistics refer to the probability distribution of the values of each pixel.
i.e intensity of pixel at different points. They refer to the color features of the images.

3.2 First order statistics

First-order features (F1) are calculated from the original image values. They do not consider the relationships with neighbor pixels. Features derived from this approach include moments such as mean, standard deviation, energy, entropy, skewness and kurtosis of an image $I_i(x,y)$ with the size MxN. These statistics are represented as

$$mean(\mu) = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N} I_i\,(x,y)}{M*N} \quad (1)$$

$$standard\ deviation(\sigma) = \sqrt{\frac{\sum_{x=1}^{M}\sum_{y=1}^{N} I_i\,(x,y)-\mu}{M*N}} \quad (2)$$

$$Energy(e) = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N} I_i^2\,(x,y) \quad (3)$$

$$Entropy = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N} I_i\,(x,y)(-\ln I_i\,(x,y)) \quad (4)$$

$$skewness = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N} I_i\,(x,y)-\mu^3}{M*N*\sigma^2} \quad (5)$$

$$Kurtosis = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N} I_i\,(x,y)-\mu^4}{M*N*\sigma^4} \quad (6)$$

IV. SIMILARITY MEASUREMENTS

4.1 City block distance

$$\delta d = \sum_{i=1}^{n}(|Qi - Di|) \quad (7)$$

This distance is also called Manhattan distance. This distance metric is computed using the sum of absolute differences between two feature vectors of images.

4.2 Canberra distance

The city block distance metric gives a large value for the similar images which creates the dissimilarity between similar images. Hence, each feature vector pair is normalized by dividing it by the sum of a pair of features.

$$\delta d = \sum_{i=1}^{n}\frac{(|Qi-Di|)}{|Qi|+|Di|} \quad (8)$$

4.3 Minkowski distance

The Minkowski distance is calculated as

$$\delta d = [\sum_{i=1}^{n}(Q_i - D_i)\,p]^{\frac{1}{p}} \quad (9)$$

where p is a positive integer. In this work p =3 is considered.

where Q and D are the query feature vectors and database feature vectors respectively[20].

After finding the similarity measurement, the minimum distance top 150 image are ranked. Then, to extract the Haralick texture features, the top 150 images are only considered.

V. HARALICK TEXTUAL FEATURES

Gray-level co-occurrence matrix(GLCM) gives the relative frequencies of occurrence of grey level combinations among pairs of image pixels. This matrix considers relationships of image pixels in different directions, such as horizontal, vertical, diagonal and anti-diagonal. Suppose the input image has M and N pixels in the horizontal and vertical directions respectively. Suppose that the grey level appearing at each pixel is quantized to Z levels, Assume *Nx* = 1,2,,3....M is a horizontal space domain and *Ny* = 1,2,3,....N is a vertical space domain and G = 0,1,2,...Z be the set of Z quantized gray levels. [20] In a given distance (*d*) and direction the GLCM is calculated using gray scale pixel i,j expressed as the number of co-occurrence matrix element as follows. The distance (*d*) can range from 1 to 8 and each pixel has eight neighbouring pixels denoting eight values. Theyare 0º, 45º , 90º , 135º , 180º , 225º , 270º or 315º [21, 22]. In this paper *d* = 1 and =90◦ are considered.

$$P(i,j|d,\boldsymbol{\theta}) = \frac{\boldsymbol{P(i,j)|d,\theta}}{\sum_i \sum_j \boldsymbol{P(i,j|d,\theta)}} \quad (10)$$

Haralick proposed 14 kinds of GLCM parameters [20] among which the following 5 parameters are mainly used.

1) Moment of inertia (contrast)

$$I = \sum_i \sum_j (i-j)^2\, P(i,j) \quad (11)$$

Image contrast can be interpreted as the sharpness of the image : the deeper grooves of the image texture, the greater contrast is.

2) Energy:

$$E = \sum_i \sum_j [(P(i,j)]^2 \quad (12)$$

Energy is the measure of gray distribution uniformity of image. The coarser the texture is, the more energy it contains

3) Entropy:

$$E = \sum_i \sum_j [P(i,j)] log P(i,j) \quad (13)$$

Entropy is a measure of the amount of information of an image. Entropy relates to the texture information. If there is no texture information, the entropy is zero.

4) Correlation:

$$C = (d,\boldsymbol{\theta}) = \frac{\sum_{i,j}(1-\mu_x)(j-\mu_y)P(i,j)}{\sigma_x \sigma_y} \quad (14)$$

Where

$$\mu_x = \sum_i \sum_j iP(i,j), \mu_y = \sum_i \sum_j jP(i,j) \quad (15)$$

$$\sigma_x^2 = \sum_i \sum_j (i-\mu_x^2) P(i,j), \sigma_y^2 = \sum_i \sum_j (i - \mu_y^2\, P(i,j) \quad (16)$$

Correlation is used to measure the degree of similarity of the elements in GLCM.

5) Homogeneity:

$$H_o = \sum_i \sum_j \frac{P(i,j)}{1+|i-j|} \quad (17)$$

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

VI. EXPERIMENTAL RESULTS

In this work, corel database consists of 1000 images are considered. It consists of 10 classes, each class has 100 images. To measure the retrieval effectiveness of the CBIR system 5 different query images from each classes are used. It is tested for 50 query images. The query and database image matching are done using different distance metrics like City block distance, Canberra distance and Minkowski distances. The minimum distance top ranked 150 images only are considered for the extraction of texture features. Then, again the same image matching process is done for these texture features. Finally, images are arranged in the order of the lowest distances to highest distances.

If there are *Ci* classes in the total image database where *i* = 1 *to* 10, then the query image in particular class *Cj* is given. After CBIR process, the relevant images of *Cj* and images from other *Ci* classes are retrieved. In corel database, each class consists of 100 images. If top *Ti* belongs to *Cj* then all retrieved images are relevant images. Experiment is done for different retrieved images and their corresponding relevant images are found.

$$Precision = \frac{No.of\ retrieved\ relevant\ images\ o\ of\ class\ C_J}{No.of\ retrieved\ images\ o\ of\ class\ C_j} \quad (18)$$

$$Recall = \frac{No.of\ retrieved\ relevant\ images\ o\ of\ class\ C_j}{No.of\ relevant\ images\ of\ class\ C_J} \quad (19)$$

$$Accuracy = \frac{precision\ +recall}{2} \quad (20)$$

$$F-score = 2 * \frac{precision\ *recall}{precision\ +recall} \quad (21)$$

Figure 2 shows the sample images used as query images. Figure 3 gives the Graphical user interface (GUI) of the CBIR system developed for cascaded features to retrieve the images.

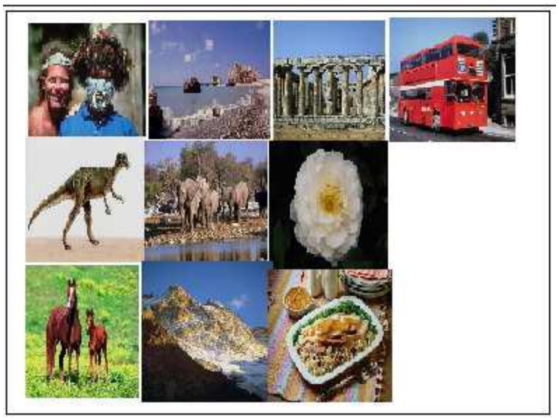

Figure 2. Sample query images

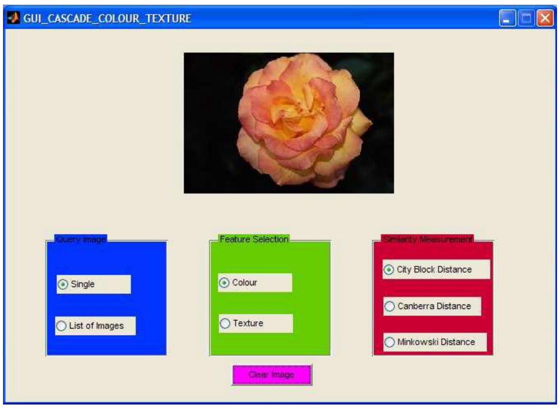

Figure 3. GUI of proposed CBIR system

Figure 4 and Figure 5 show the accuracy and F-score obtained by the different features like color only, texture only and cascaded features of different similarity measurement. It is observed that the cascaded features using Canberra distance gives 84% of accuracy and F-Score value as 75% in image retrieval.

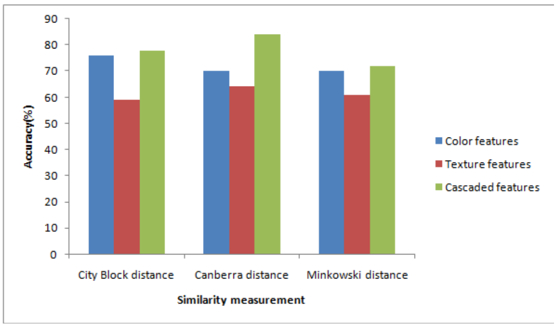

Figure 4. Accuracy of the different similarity measurements

Figure 6 shows the output of the retrieved images from the proposed CBIR system. Figure 7 to Figure 9 show the crossover point of the precision recall values of the cascaded features using city block distance, Minkowski distance and Canberra distances. Higher the cross over point better is the performance[7].

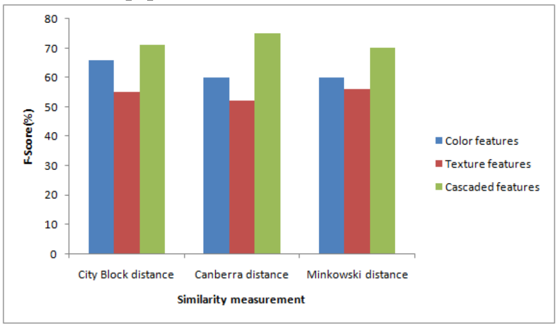

Figure 5. F-Score of the different similarity measurements

The cross over point of precision and recall using Canberra distance is 0.45 whereas using city block distance is 0.41 and using Minkowski is 0.40. It is observed that the cascaded features using Canberra distance gives better results.

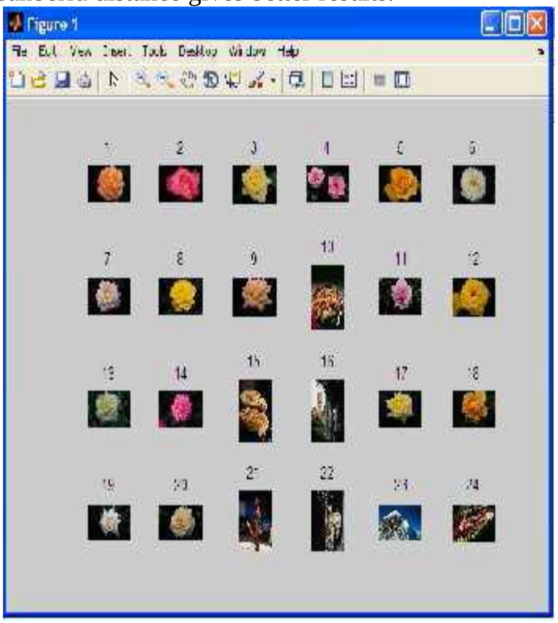

Figure 6: Images retrieved using cascaded features

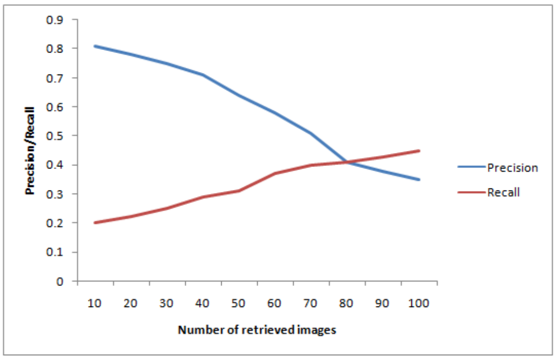

Figure 7: Average Precision Recall values of cascaded features using city block distance.

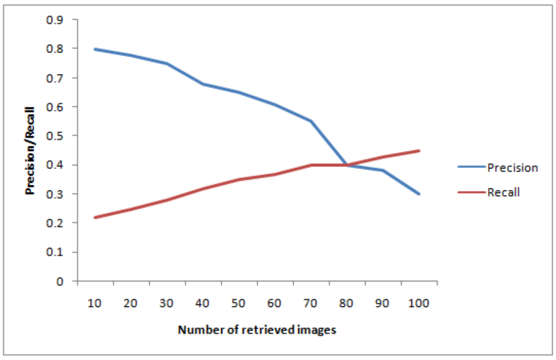

Figure 8: Average Precision Recall values of cascaded features using Minkowski distance.

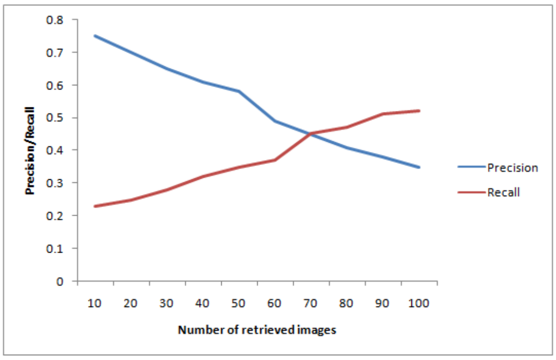

Figure 9: Average Precision Recall values of cascaded features using Canberra distance.

VII. CONCLUSION

In this paper, the six first order statistical features which signify the color features of images are used. Similar images are retrieved using different distance metric like Canberra distance, city block distance and Minkowski distance. Then, minimal distance top ranked 150 images are only considered for the extraction of texture features. Hence, it reduces the computational time. It Again, the similarity measurement is calculated using same distance metrics. Thus, the features are extracted using cascading approach. It is found that the cascading features with Canberra distance gives better results.

REFERENCES

[1] W.Nilback, et.al, "The qbic project: querying im- ages by content using color, texture and shape," *SPIE Proceedings on storage and Retrieval for image and video Databases*, pp. 173–187, 1993.

[2] A.Pentland, et.al, "Photobook : tools for content based image retrieval," *International Journal of Computer Vision*, vol. 18, no. 3, pp. 233–254, 1996.

[3] A. Gupta, R.Jain, "Visual information retrieval" *Communications of the ACM*, vol. 40, no. 5, pp.70–79, 1997.

[4] J.R.Smith,S.F.Chang, "Visualseek: a fully auto mated CBIR query system," *Proceedings of Multi- media Conference*, 1996.

[5] W.Y.Ma, B.Manjunath, "Netra, a toolbox for navigating large image databases," *Proceedings of International conference on image Processing*, , no.5, pp. 568–571, 1997.

[6] J.Z.Wang, J.Li, G.Wiederhold, "Simplicity: Semantics-sensitive integrated matching for image libraries," *IEEE transaction on Pattern Mach. In- tell.*, vol. 23, no. 9, pp. 947–963, 2001.

[7] Vibha Bhandari , Sandeep B.Patil, "Comparison of cbir techniques using dct and fft for feature vec- tor generation," *International Journal of Emerging Trends and Technology in Computer Science*, vol.1, no. 4, pp. 90–96, 2012.

[8] Anit Sharma, Gurpreet Singh, "Comparative study:Content based image retrieval using low level features," *International Journal of Engineering Re- search and Applications*, vol. 3, no. 2, pp. 962–967,2013.

[9] H.B.kekre, Dhirendra Mishra, "Performance comparison of sectorization of dct and dct wavelet transformed images in cbir," *International Jour- nal of Computer Applications*, vol. 23, no. 4, pp.26–34, 2011.

[10] Vrushali Yashwant Ernade, P.R. Badadapure, " Content Based Image Retrieval using Neural Network", *International Journal of Scientific & Engineering Research*, vol.4, no.8, pp. 571-575 2013.

[11] Sai, Patil, "Image Retrieval using 2D Dual-Tree Discrete Wavelet Transform", *International Journal of Computer Applications*, vol. 14, no.6, pp. 1-7, 2011.

[12] Nidhi Singh, Kanchan Singh, Ashok K.Siha, " A Novel approach for Content Based Image Retrieval", *Procedia Technology (Elsevier)*, vol.4, pp.245-250, 2012.

[13] Shaila S G, Vadivel A, "Block Encoding of Color Histogram for Content Based Image Retrieval Applications", *Procedia Technology (Elsevier)*, vol.6, pp.526-533, 2012.

[14] Ke Lu, Ning He, Jian Xue, "Content-based similarity for 3D model retrieval and classification", *Journal of Progress in Natural Science (Elsevier)* , vol.19, pp.495-499, 2009.

[15] R.Malini, C.Vasanthanayaki, "An Enhanced Content Based Image Retrieval System using Color Features", *International Journal of Engineering and Computer Science*, vol. 2, no.12, pp.3465-3471, 2013.

[16] H . B . Kekre, Dhirendra Mishra, "Discrete Sine Transform Sectorization for Feature Vector Generation in CBIR", *Universal Journal of Computer Science and Engineering Technology*, vol.1, no.1 pp.6-15, 2010.

[17] Swapna Borde, Dr. Udhav Bhosle, "Image Retrieval using Contourlet Transform", International Journal of Computer Applications, vol. 34, no.5, pp.37-43, 2011,

[18] M.Rakhee, V.K. Govidan, Bajju Karun, "Enhancing the Precision of Walsh Wavelet Based approach for Color and Texture Extraction in CBIR by including a Shape Feature, Journal of Cybernetic and Information Technologies, vol.13, no.2, pp.97-105, 2013.

[19] H.Mohamadi, A.Shahbahrami, J.Akbari, "Image retrieval using the combination of text-based and content-based algorithms," *International Journal of AI and Data mining*, pp. 1–8, 2013.

[20] Fazal Malik, Baharum Baharudin, "Analysis of Distance metrics in Content-based image retrieval using statistical quantized histogram texture features in DCT domain", Journal of King Saud University, vol.25, no.2, pp.207-218, 2013.

[21] R M Haralick, K.Shanmugam, "Texture feature for image classification," *IEEE Transactions on Systems*, vol. SM-3, no. 6, pp. 768–780, 1973.

[22] S.Selvarajah, S.R.Kodituwalku, "Analysis and Comparison of Texture features for Content Based Image Retrieval", International Journal of Latest Trends in Computing, vol.2, no.1, pp.108-113, 2011.

Mr.N.Puviarasan received M.S from BITS Pilani and M.S(Software systems) from Annamalai University. He is working as Associate Professor in the Dept. of Computer Science and Engineering, Annamalai University. His area of research is image processing. He has 25 years of experience in teaching. He is involved in research activities for the past 7 years.

Dr.R.Bhavani received B.E and M.E from NIT Trichy and Ph.D from Annamalai University. She is working as Professor in the Dept. of Computer Science and Engineering, Annamalai University. Her area of research is image processing. She has 24 years of experience in teaching. She has published 30 papers in national and international journals.