



CONTENT BASED IMAGE RETRIEVAL USING COLOR AND TEXTURE

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ABSTRACT

The performance of Content-Based Image Retrieval (CBIR) system is depends on efficient feature extraction and accurate retrieval of similar images. Content based image retrieval is the task of retrieving the images from the large collection of database on the basis of their own visual content. This paper combines color features using Color Descriptor (CN) and texture features using Gray Level Co-occurrence Matrix (GLCM) to obtain better retrieval efficiency. From large database, using these feature vectors near about similarly matched images are retrieved. It is observed that combination of color features with the texture provides approximately similar results with very less processing time if we compare with individual approach.

Keywords: *CBIR , Color Descriptor(CN), feature vector, Gray Level Co-occurrence Matrix(GLCM)*

I. INTRODUCTION

In the recent years, the amount of digital images has grown rapidly. The main reasons for that, one may mention digital cameras and high-speed Internet connections. All those elements have created a effective way to generate and publish visual content worldwide. Huge amount of information such as audio, video ,pictures are available to the users from internet. Much of that visual information contains largest and most heterogeneous image database so far considered. In such case, there is a very much need for image retrieval systems ,which could be satisfied by content-based image retrieval (CBIR) systems. In CBIR systems, the image descriptor is a very crucial element. It is responsible for assessing the similarities between the images.

Image retrieval techniques are divided into two categories which are text and content-based categories. The text-based approach comprises some special words like keywords. Annotations and Keywords are to be distributed in each every image, at the time the images are stored in a database. The annotation operation is time consuming and tedious one. Furthermore, the annotations are sometimes not sufficient due to which some image features may not be mentioned in annotations. Extracted low-level features are used to index images using visual contents, such as shape, texture, color and so on. One of the difficult task is to extracting all the visual features from image and also having a problem called as semantic gap. In the semantic gap, presenting high-level visual concepts using low-level visual concept is very difficult. In order to remove these barriers, some researchers merge multiple techniques together using different features. That combination improves the performance compared to each technique separately.

A typical CBIR system which automatically extract visual attributes such as shape ,color, spatial information and texture of each and every image in the database based on its pixel values and stores them into a database

within the system which is called as feature database. The feature vector database obtained for each of the visual attributes of each image is very much smaller in size compared to the image data which contains an abstraction of the images in an image database; each and every image is represented by a compact representation of its contents like color, texture, shape and spatial information in the form of a fixed length real-valued multi-component feature vectors. The users usually applies query image to the system. The system usually extract the visual attributes of the query image in the same mode as it does for each database image and then using different similarity metrics finds the similar images in the database

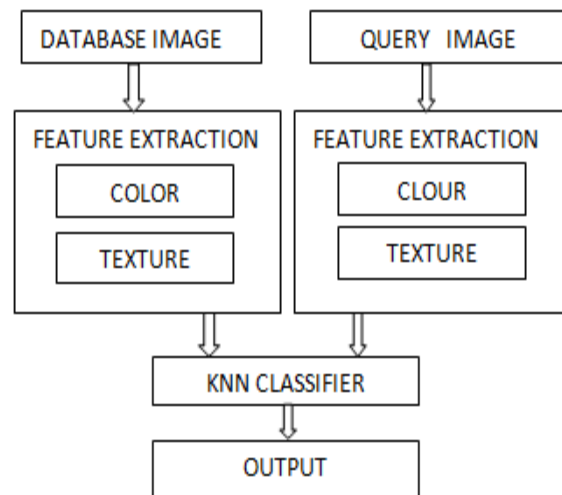


Fig.1.Proposed CBIR System

Basically CBIR uses two approaches for retrieving the images from the image data base. One is Text-based approach (index images using keywords), *that* use the keywords descriptions as a input and then the desired output is obtained in the form of similar types of images. Content-Based Approach is another approach, which uses image as an input query and it generate the output of similar types of images. An image consists of complex structure and also having various levels of details. Single resolution is not sufficient to determine the details present within an image. Multiple resolution analysis overcomes this drawback. Multiple resolution analysis analyses images at more than one resolution so that the features that are left undetected at one level get spotted at another level. This paper exploits the combination of color and texture features at more than one resolution of image in order to combine advantages of multiple features to form efficient and powerful feature vector for image retrieval.

In this paper, color information is extracted by using Color Descriptor(CN) and texture is extracted by using method GLCM. Both the features are combined to obtain effective feature vector.KNN classifier is used to classify the images which use Euclidean distance to find out similarity between features.

II. RELATED WORK:

The There are number of methods which has been proposed to extract the features of images from very large database.

A content-based image retrieval system has been proposed by Yamamoto *et.al*[2] , which takes account of the spatial information of colours by using multiple histograms. The spatial information of colors is captured by



dividing an image into two rectangular sub-images recursively. Using a straight line vertically or horizontally, the given image is divided into two regions, even when each sub image, the division process continues recursively until each region has a homogeneous color distribution or the size of each region becomes smaller than that a given threshold value. As a result of which the color distribution of the image is derived with binary tree. The tree structure facilitates the evaluation of similarity among images.

G. Pass *et.al* [3] proposed a novel method to describe spatial features in a more precise way. That model is not variant to scaling, rotation and shifting.

S. Nandagopalan, *et.al* [4] proposed a novel technique for generalized image retrieval based on semantic contents is offered. The grouping of color, texture, and edge histogram descriptor is performed. There is a necessity to include new for better retrieval efficiency features in future. Using computer vision and image processing algorithms, the image properties are analyzed. Anticipated for color the histogram of images are calculated, for texture co-occurrence matrix based entropy, energy etc are calculated and for edge density it is Edge Histogram Descriptor (EHD) that is found.

Heng Chen and Zhicheng Zhao *et.al*[5] Authors described relevance feedback method for image retrieval. Relevance feedback (RF) is an efficient method for content-based image retrieval (CBIR), a The semantic gap between low-level visual feature and high-level perception is minimized by this method. The proposed algorithm is SVM-based RF algorithm used to advances the performance of image retrieval. To stabilize the proportion of positive samples and negative samples, a model expanding method have adopted in classifier training. Based on adaptive weighting, a fusion method for multiple classifiers is proposed to vote the final query results.

Xiang-Yang Wang, *et.al* [6] have proposed a new content-based image retrieval technique using color and texture information, for achieving higher retrieval efficiency. Initially, the image is altered from RGB space to adversary chromaticity space and the individuality of the color contents of an image is space. In next, the texture attributes are extracted using a rotation-invariant and scale- incarcerated by using Zernike chromaticity distribution moments.

S. Manoharan, S. Sathappan *et.al* [7] implemented the high level filtering wherever they are using the Anisotropic hierarchical Kaman filter, particle filter proceeding and Morphological Filters with feature extraction method based on gray level feature and color and related to this the results were normalized.

Jisha. K. P, *et.al* [8] proposed the content based image retrieval system which is semantic using Gray Level Co-occurrence Matrix (GLCM) for texture information extraction. Using texture features, semantic explanation is given to the extracted textures. The images are regained regarding to user contentment and thereby reducing the semantic gap between low level features and high level features.

III. FEATURE REPRESENTATIONS[10]

Feature extraction and representation is the most fundamental process behind CBIR systems. As earlier mentioned, features are properties of the image extracted with image processing algorithms, such as colour, texture, shape, and edge information. We have focused on two general features representation terms that have been extensively studied in the literature: color and texture. However, there is no single best feature which will

give accurate results in any general setting. Usually, a combination of features is minimum required to provide adequate retrieval results since perceptual subjectivity permeates throughout this problem.

3.1 COLOR DESCRIPTOR(CN) :

The first and mostly straightforward feature for indexing and retrieving images is color. All other information is computed by image processing algorithms that generally starts with the color information contained in an image. When the image contains especially just the object, color moments have been successfully used in most of retrieval systems. Color moment, Color Histograms have been proved to be efficient and effective in representing color distributions of images.

The CN descriptor assigns to each pixel a 11-D vector, of which each dimension encodes one of the eleven basic colors: black, blue, brown, grey, green, orange, pink, purple, red, white and yellow. As with CN, we first compute CN vectors of pixels surrounding the keypoint, with the area proportional to the scale of the keypoint. Then, we take the average CN vector as the color feature. The two descriptors of a keypoint are individually quantized, binarized, and fed into our system, respectively[12].

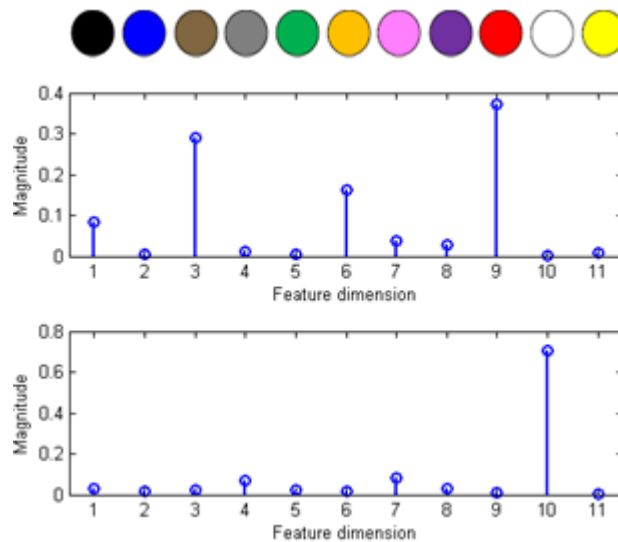


Fig.2. An example of visual match

Above figure 2 shows a matched SIFT pair between two images. The 11-D color name descriptors of the matched keypoints in the left (middle) and right (bottom) images are presented above. Have also shown the prototypes of the 11 basic colors. In this example, the two matched keypoints differs a lot in color, thus considered as incorrect positive match.

For an image selected from an image database, because the visual requirements of people are not satisfied by RGB color spaces, the image is converted from an RGB space to other color spaces in image retrieval. RGB colors are called primary colors and are additive. By varying their combinations, other colors can be obtained. Divide the input image into 3 levels as $I(i, j, p) \leq 85$ then to $I_H(i, j, p) = 1$, if $I(i, j, p) \leq 170$ then to $I_H(i, j, p) = 2$, and if $I(i, j, p) > 170$ then to $I_H(i, j, p) = 3$. Where i, j, p are the pixels from red, green, blue planes respectively. Now to find unique color for above levels Then use,

Color_Number = $6 * \text{Red_Level} + 3 * \text{Green_level} + 1 * \text{Blue_level}$ and then find Histogram

3.2 GRAY LEVEL CO-OCCURRENCE MATRIX (GLCM):

Texture is one of the important characteristics used in identifying objects or in detecting regions of interest in an image. Texture contains crucial information about the structural arrangement of surfaces. Textural features contain information about the spatial distribution. The twelve textural features proposed by Haralick [13] contain information about image texture characteristics such as homogeneity, gray-tone linear dependencies, contrast, number and nature of boundaries present and the complexity of the image. In texture based approach, contextual features contain information derived from blocks of pictorial data surrounding the area being analyzed [13].

Few of the common statistics applied to co-occurrence probabilities are discussed below:

1) Energy:

$$Energy = \sum_i \sum_j P^2(i, j) \quad (1)$$

This statistic is also called Uniformity or Angular second moment. It is used to measure the textural uniformity that is pixel pair repetitions. Energy detects disorders in textures. It reaches a maximum value equal to one. High energy values occur when gray level distribution has a constant or periodic form. It has a normalized range.

The GLCM of less homogeneous image shall have large number of small entries.

2) Entropy:

$$Entropy = \sum_i \sum_j (i, j)_{(2)} \log[P(i, j)] \quad (2)$$

This statistic measures the disorder or complexity of an image. It is large when the image is not texturally uniform and many GLCM elements will have very small values. Complex textures tend to have high entropy. It is strongly, but inversely correlated to energy.

3) Variance:

$$Variance = \sum_i \sum_j (i - \mu)^2 g_{ij} \quad (3)$$

where μ is the mean of g_{ij}

Heterogeneity is measured by it and variance is strongly correlated with standard deviation. When the gray level values differ from their mean, variance increases.

5) Homogeneity:

$$Homogeneity = \sum_i \sum_j \frac{1}{1 + (i - j)^2} g_{ij} \quad (4)$$

This statistic is also called as Inverse Difference Moment. It is used to measure an image homogeneity as it assumes larger values for smaller gray tone differences in pair elements. Homogeneity is more sensitive to the presence of near diagonal elements in the GLCM. Homogeneity has maximum value when all elements in the image are same. Contrast and homogeneity of GLCM are strongly, but inversely, correlated in terms of equivalent distribution in the pixel pairs population. If energy is kept constant, homogeneity decreases if contrast increases.



6) Correlation:

$$\text{Correlation} = \frac{\sum_i \sum_j (ij) g_{ij} - \mu_x \mu_y}{\sigma_x \sigma_y} \quad (5)$$

where μ_x , μ_y , σ_x and σ_y are the means and standard deviations of g_x and g_y . It is a measure of gray tone linear dependencies in the image.

7) Mean:

$$\text{Mean} = \sum \sum i P(i) \quad (6)$$

It represents amount of brightness present in an image. The rest of the textural features are secondary and derived from those listed above.

8) Sum Average:

$$\text{SumAverage} = \sum_{i=2}^{2N_g} i g_{x+y}(i) \quad (7)$$

9) Sum Entropy:

$$\text{SumEntropy} = - \sum_{i=2}^{2N_g} g_{x+y}(i) \log\{g_{x+y}(i)\} \quad (8)$$

10) Sum Variance:

$$\text{SumVariance} = \sum_{i=2}^{2N_g} (i - \text{SumAverage})^2 g_{x+y}(i) \quad (9)$$

11) Difference Variance:

$$\text{DifferenceVariance} = \text{variance of } (g_{x-y}(i)) \quad (10)$$

12) Difference Entropy:

$$\text{DifferenceEntropy} = - \sum_{i=0}^{2N_g-1} g_{x-y}(i) \log\{g_{x-y}(i)\} \quad (11)$$

Energy and Contrast are to be the most important parameters for treating different textural patterns. The general rules used in to select textural features can be stated as follows: Energy is preferred to entropy. The value of energy belongs to normalized range. It is similar to variance however it is preferred due to reduced computational load and its effectiveness as a spatial frequency measure. Energy and contrast are the most significant parameters.

3.3 SIMILARITY MEASUREMENT:

To measure the similarity between the query image and the database images, the difference is calculated between the query feature vector and the database feature vectors calculated from image database by using the different distance metrics. The small difference between these two feature vectors indicates a large similarity and a small distance. The vectors of the images with a small distance are most similar to the query image. Euclidean distance is a most commonly used for similarity measurement in image retrieval because of its efficiency and effectiveness. It finds the distance between two vectors of images by calculating the square root

of the sum of the squared absolute differences. Let any query feature vector be represented by Q and the database feature vector by D to calculate the difference between the two vectors for similarity using the Euclidean distance as:

$$\Delta d = \sqrt{\sum_{i=1}^n (Q_i - D_i)^2} \quad (12)$$

IV. EXPERIMENTAL RESULTS:

We have provided a database which is used to test the proposed method. This database consists 72 images of different types. Here we are comparing color descriptor and GLCM. We have inputted Query Image as follows:

Input Query Image:



Fig.3. Query image to perform content based image retrieval.

Experimental Results of Color Extraction:

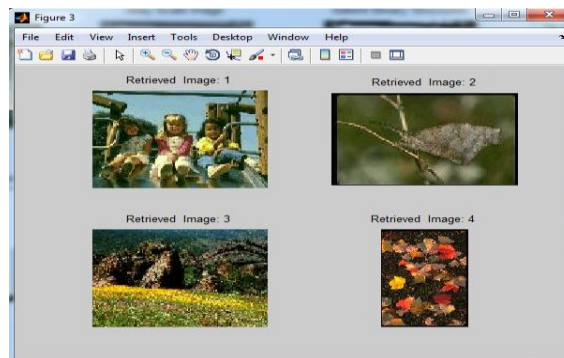


Fig.4. Retrieved results using color descriptor

Experimental Results of Texture Extraction:

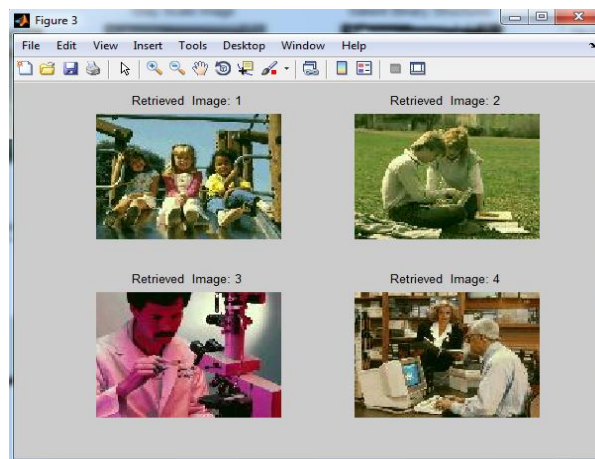


Fig.5. Retrieved results using GLCM

Experimental Results of Color and Texture Extraction(Combined Approach):

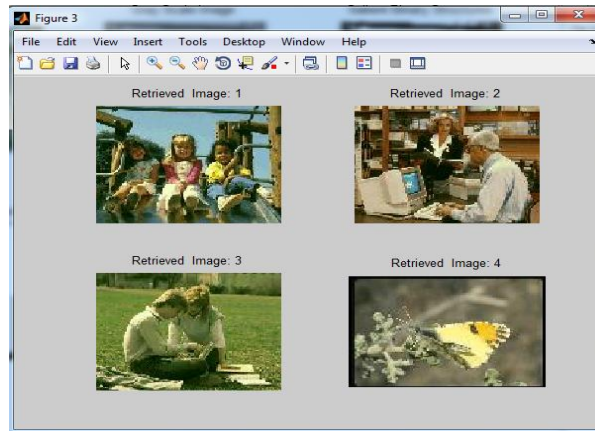


Fig.6.Retrieved results using integrated approach

V. CONCLUSION

In this paper, we have presented a method for image retrieval using combination of texture and color features in multiple resolution analysis framework. It is an integrated approach used to extract color and texture feature from images. By using single feature, correct results can never produced. So multi feature extraction is more beneficial to perform image retrieval. Color features are extracted using color descriptor and texture features are extracted using GLCM. The similarity measures made between feature vectors of input images and database images using Euclidean distance. Finally, a practical results proved that the better retrieval performance obtained for maximum test images based on multi-features compared to single content features.

REFERENCES

- [1] M. E. J. Wood, N. W. Campbell, and B. T. Thomas, "Iterative refinement by relevance feedback in content-based digital image retrieval," In ACM Multimedia 98, pages 13–20, ACM, 1998.
- [2] H. Yamamoto, H. Iwasa, N. Yokoya, and H. Takemura, "Content- Based Similarity Retrieval of Images Based on Spatial Color Distributions," ICIAP '99 Proceedings of the 10th International Conference on Image Analysis and Processing1.
- [3] G.Pass, and R. Zabith, "Comparing images using joint histograms," Multimedia Systems, Vol.7, pp.234-240, 1999.
- [4] S. Nandagopalan, Dr. B. S. Adiga, and N. Deepak, "A Universal Model for Content-Based Image Retrieval," World Academy of Science, Engineering and Technology, Vol.2,Issue3, 2008-10-29.
- [5] Heng chen, zhicheng zhao "An effective relevance feedback algorithm for image retrieval," IEEE journal ,978-1-4244-6853,9/10/ 2010.4
- [6] Xiang-Yang Wang, Hong-Ying Yang, Dong-Ming Li "A new content-based image retrieval technique using color and texture information", Computers & Electrical Engineering, Volume 39, Issue 3, April 2013, Pages 746-761[5].



- [7] S. Manoharan, S. Sathappan, "A Novel Approach For Content Based Image Retrieval Using Hybrid Filter Techniques", 8th International Conference on Computer Science & Education (ICCSE 2013) ,April 26-28, 2013, Colombo, Sri Lanka6
- [8] Jisha.K.P, Thusnavis Bella Mary. I, Dr. A.Vasuki, "An Image Retrieve AI Technique Based On Texture Features Using Semantic Properties", International Conference on Signal Processing, Image Processing and Pattern Recognition [ICSIPR], 2013.8
- [9] Monika Daga, Kamlesh Lakhwani, "A Novel Content Based Image Retrieval Implemented By NSA Of AIS", International Journal Of Scientific & Technology Research, Volume 2, Issue 7, July 2013 ISSN 2277-8616.[9]
- [10] M. Stricker, and M. Orengo, "Similarity of color images," SPIE Storage and Retrieval for Image and Video Databases III, vol. 2185, pp.381-392, Feb. 1995.
- [11] Roshi Choudhary, Nikita Raina, Neeshu Chaudhary, Rashmi Chauhan, Dr. R H Goudar` An Integrated Approach to Content Based Image Retrieval," International Conference on Advances in Computing, Communications and informatics (ICACC1), 978-1-4799-3080-7,2014.
- [13] R. M. Haralick, K. Shanmugam and I. Dinstein "Textural features for Image Classification", IEEE Transactions on Systems, Man and Cybernetics, Vol.3, pp. 610-621, November 1973