International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-3 Issue-2, July 2013

Feature Extraction for Image Retrieval Using Color Spaces and GLCM

Madhura C, Dheeraj D

Abstract— Due to the enormous increase in the size of image databases as well as its vast deployment in various applications, the need for Content Based Image Retrieval (CBIR) development arose. This paper describes a hybrid feature extraction approach of our research and solution to the problem of designing a CBIR system manually. Two features are used for retrieving the images such as color and texture. Color feature is extracted by using different color space such as RGB, HSV and YCbCr. Texture feature is extracted by applying Gray Level Co-occurrence Matrix(GLCM). The image is retrieved by combining color and texture feature and the color space which gives the best result as analyzed using precision and recall graph.

Index Terms—Color Spaces, Euclidean Distance, Image Retrieval, Precision, Recall.

I. INTRODUCTION

The term Content Based Image Retrieval (CBIR) originated in 1992, by T. Kato [1]. It is a process of retrieving images from a database based on the features that are extracted from the images. Two types of features are present in the image ie., General and Domain Specific. General features or Low Level Features such as Color, Texture and Shape. Domain Specific or High Level Features such as emotions etc, these features are difficult to extract. The user provides a "query" image and the search is based upon that query (e.g. Fig. 1.1). CBIR system is used in many applications [2] such as Fingerprint Identification, Biodiversity Information Systems, Digital Libraries, Crime Prevention, Medicine, Historical Research, Trademark Image Registration, Automatic Face Recognition Systems, Fashion and Graphic Design, Architectural and Engineering Design, Remote sensing and Management of Earth Resources, Cultural Heritage, Publishing and Advertising etc. In the present work the experiments of CBIR have been used to evaluate the effect of different color space on model performance. In this paper, Literature Survey of CBIR is dealt in Section 2. Section 3 describes the Proposed Methods. Section 4 focuses on Similarity Measurement. Section 5, provide particulars of Experiments conducted followed by result. Section 6 presents Conclusion and Future Work and Finally, the References.

Literature Survey

Content based image retrieval for general-purpose image databases is a highly challenging problem because of the large size of the database, the difficulty of understanding images, both by people and computers, the difficulty of formulating a query, and the issue of evaluating results properly. A number of general-purpose image search engines have been developed. In the commercial domain, QBIC [3] is one of the earliest systems. Recently, additional systems have been developed such as T.J. Watson [4], VIR [5], AMORE [6], and Bell Laboratory WALRUS [7]. In the academic domain, MIT Photobook [8] [9], is one of the earliest systems. Berkeley Blobworld [10], Columbia Visualseek and Webseek [11], Natra [12], and Stanford WBIIS [13] are some of the recent well known systems. The common ground for CBIR is to extract a signature for every image, based on its pixel values, and to define a rule for comparing images. The signature can be color, texture, shape or any other information with which two images could be compared. Distance metric or matching criteria is the main tool, for retrieving similar images from the large image databases, for all the above categories of search.

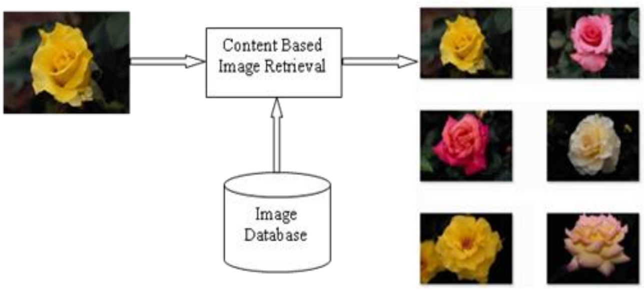


Fig. 1.1 Example of CBIR system

II. PROPOSED METHOD

There are different methods for image retrieval using low level features color, texture and shape. In order to use good color space for specific application, color conversion is needed. In this paper color and texture features are used to retrieve the images. In color different color space are used, by converting the color images from RGB to another color spaces like Gray, HSV ,HSI, YCbCr ,Lab, CMY etc, and processing these images gives better results. In texture the co-occurrence matrix is used.

A. *Color Space*

Color Space is defined as model for representing colors in terms of intensity values. A color model is an abstract mathematical model describing the way colors can be represented as tuples of numbers, typically as three or four values of color components. Three different color space are used in this paper they are: RGB, HSV, YCbCr.

Manuscript published on 30 July 2013.
*Correspondence Author(s)
Madhura C, Department of Information Science and Engineering, P.E.S Institute of Technology, Bangalore, Karnataka, India.
Asst. Prof. Dheeraj D, Department of Information Science and Engineering, P.E.S Institute of Technology, Bangalore, Karnataka, India.

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)

RGB Color Space

RGB is additive in nature. It is sum of three primary colors Red (R), Green (G) and Blue (B). The range of values of each of this components lies within 0 to 255. Any other color space can be obtained from a linear or non-linear transformation from RGB. It is one of most widely used color space for processing and storing the digital image data [14]. However, high correlation between the red, green and blue colors. This color space is device dependent which means that the same signal or image can look different on different devices. In RGB chrominance and luminance component are mixed.

HSV Color Space

HSV stands for Hue, Saturation and Value. Hue and Saturation defines chrominance, Value or intensity specifies luminance [15]. Hue is used to distinguish colors, Saturation measures the percentage of white light added to the pure color, Value is the light intensity. Eq. (1), (2) & (3) shows the transformation from RGB color space to HSV color space.

$$h = \begin{cases} 0, \textit{if } \max = \min \\ (60^\circ \times \dfrac{g-b}{\max - \min} + 0^0) \bmod 360^\circ, \textit{if } \max = r \\ 60^\circ \times \dfrac{b-r}{\max - \min} + 120^0, \textit{if } \max = g \\ 60^\circ \times \dfrac{r-g}{\max - \min} + 240^0, \textit{if } \max = b \end{cases} \quad (1)$$

$$s = \begin{cases} 0, \textit{if } \max = 0 \\ \dfrac{\max - \min}{\max} = 1 - \dfrac{\min}{\max}, \textit{otherwise} \end{cases} \quad (2)$$

$$v = \max \quad (3)$$

Here, max represent the greatest of r, g, b and min represent the least.

YCbCr Color Space

YCbCr color space has been defined in response to increasing demands for digital algorithms. Y is luma component which represent the luminance and computed from nonlinear RGB [16]. It is obtained as weighted sum of RGB values. Cb is difference between blue and luma component and Cr is the difference between red and luma component [14] [17]. The Y in YCbCr denotes the luminance component, and Cb and Cr represent the chrominance component. Eq. (4) shows the transformation from RGB to YCbCr color space.

$$\begin{aligned} Y &= 0.299R + 0.587G + 0.114B \\ Cr &= R - Y \\ Cb &= B - Y \end{aligned} \quad (4)$$

Here, mean and standard deviation are calculated for every component in the set of chosen color spaces. Mean of pixels color depicts principal color of the image and standard deviation depicts the variation of pixel color.

B. Texture

Texture innate property of all surfaces, describes the visual patterns and that contain important information about the structural arrangement of the surface and its relationship to the surrounding environment. E.g. clouds, leaves, bricks, fabrics etc. It is a feature that describes the distinctive physical composition of a surface. In low level feature, texture co-occurrence matrix is used for retrieval of the images.

Co-occurrence matrix

While calculating the co-occurrence matrix [18], the image is first converted into gray scale, and then co-occurrence matrix is calculated called as Gray Level Co-occurrence matrix (GLCM). Co-occurrence matrix describes spatial relationships between grey-levels in a texture image. GLCM is composed of the probability value, it is defined by p(i, j | d, θ) which expresses the probability of the couple pixels at θ direction and d interval. When θ and d is determined, p(i, j | d, θ) is showed by P i j, . Distinctly GLCM is a symmetry matrix; its level is determined by the image gray-level. Elements in the matrix are computed by using eq. (5)

$$P(\mathrm{i}, \mathrm{j} \mid \mathrm{d}, \theta) = \frac{P(\mathrm{i}, \mathrm{j} \mid \mathrm{d}, \theta)}{\sum_i \sum_j P(\mathrm{i}, \mathrm{j} \mid \mathrm{d}, \theta)} \quad (5)$$

To estimate the similarity between different gray level co-occurrence matrices, many statistical features extracted from them like Energy, Entropy, Contrast, Homogeneity are given in the eq. (6),(7), (8), (9) respectively.

Energy is the sum of squared elements or angular second moment.

$$Energy = \sum_i \sum_j \mathrm{P(i, j)}^2 \quad (6)$$

Entropy is the statistical measure of randomness.

$$Entropy = -\sum_i \sum_j P(\mathrm{i}, \mathrm{j}) \log P(\mathrm{i}, \mathrm{j}) \quad (7)$$

Contrast gives the local variations in GLCM.

$$\mathrm{Contrast} = \sum_i \sum_j (\mathrm{i} - \mathrm{j})^2 P(\mathrm{i}, \mathrm{j}) \quad (8)$$

Homogeneity is the closeness of distribution of elements.

$$\mathrm{Homogeneity} = \sum_{i,j=0}^{N-1} \frac{p_{i,j}}{1 + (\mathrm{i} - \mathrm{j})^2} \quad (9)$$

III. SIMILARITY MEASUREMENT

There are many similarity measures such as Manhattan Distance, Minkowski Distance, Chebyshev Distance etc, for matching and retrieving the similar image from the image database. In this paper, we have chosen Euclidean Distance Measurement for similarity computation. Eq. (10) shows the Euclidean Distance.

$$d = \sqrt{\sum_{i=1}^{N} (\mathrm{F_Q[i]} - \mathrm{F_{DB}[i]})^2} \quad (10)$$

Where, $F_Q[i]$ is the query image feature and $F_{DB}[i]$ is the corresponding feature in the feature vector database. N-number of images in the database.

IV. EXPERIMENTAL RESULTS

The proposed image retrieval method is implemented using OpenCV 2.4.3. The database we used in our evaluation is WANG database [19].

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)

The WANG database is a subset of the Corel database of 1000 images, which have been manually selected to be a database of 10 categories of 100 images each (Fig. 5.1). The images are of size 384 × 256 or 256 × 384 pixels.

Fig. 5.1 Images from each of the 10 Categories of WANG Database.

Performance Evaluation Metrics

The level of retrieval accuracy achieved by a system is important to establish its performance. In CBIR, precision-recall is the most widely used measurement method to evaluate the retrieval accuracy. **Precision**, P, is defined as the ratio of the number of retrieved relevant images to the total number of retrieved images [20].

$$P = \frac{\text{Number of relevant images retrieved}}{\text{Total number of images retrieved}} \quad (11)$$

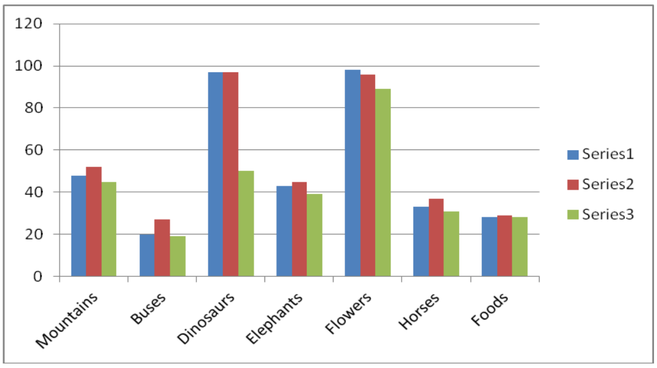
Let the number of all retrieved images be n, and let r be the number of relevant images according to the query then the precision value is: P = r / n. Precision P measures the accuracy of the retrieval.

Recall, R, is defined as the ratio of the number of retrieved relevant images to the total number of relevant images in the whole database [20].

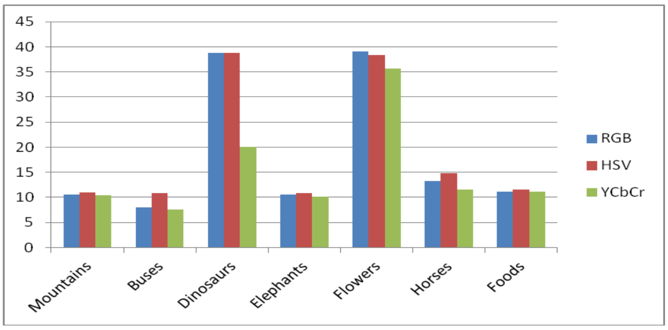
$$R = \frac{\text{Number of relevant images retrieved}}{\text{Number of relevant images in the database}} \quad (12)$$

Let r be the number of relevant images among all retrieved images according to the query, and M be the number of all relevant images to the query in the whole database then the Recall value is: R = r / M. Recall R measures the robustness of the retrieval.

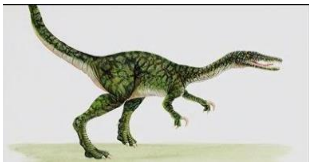
Precision graph:



Recall graph:



RGB Color Space



Query Image

Fig. 5.2 Top 10 retrieved images for RGB colos space based on similarity distance.

HSV Color Space

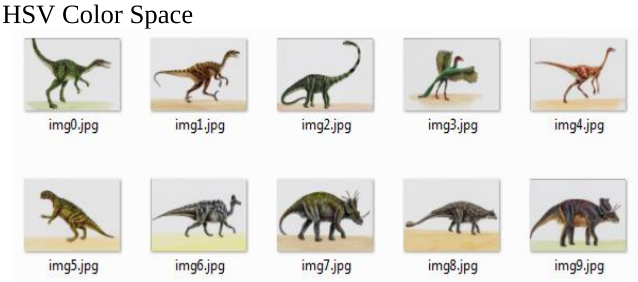


Fig. 5.3 Top 10 retrieved images for HSV colos space based on similarity distance.

YCbCr Color Space

Published By:
Blue Eyes Intelligence Engineering and Sciences Publication (BEIESP)

Fig. 5.4 Top 10 retrieved images for YCbCr colos space based on similarity distance.

V. CONCLUSION

An image retrieval method using different color space and texture has been proposed. Experimental results showed that the precision and recall for buses, horses, and food image categories HSV color space gives good results than other color spaces.

In future still more efficient color spaces and distance measures can be applied to analyze the performance of color spaces.

REFERENCES

1. T. Kato. Database architecture for content-based image retrieval. In A. A. Jambardino and W. R. Niblack, editors, Proceedings of SPIE Image Storage and Retrieval Systems, volume 1662, pages 112–123, San Jose, CA, USA, February 1992.
2. Gauri Deshpande, Megha Borse, " Image Retrieval with the use of different color spaces and the texture feature", International Conference on Software and Computer Applications, Vol. 9, pp. 273-278, 2011.
3. M. Flickner, H. Sawhney, W. Niblack, J. Ashley, Q. Huang, B. Dom, M. Gorkani, J. Hafner, D. Lee, D. Petkovic, and P. Yanker, “Query by image and video content: The QBIC system,” IEEE Computer, vol. 28, no 9, pp.23-32, Sep. 1995.
4. J. Smith and C. Li, “Image Classification and Querying Using Composite Region Templates,” Int. J. Computer Vision and Image Understanding, vol. 75, no. 2, pp.165-174, July 1999.
5. A. Gupta, and R. Jain, “Visual information retrieval,” Comm. Assoc. Comp. Mach.,vol. 40, no. 5, pp. 70–79, May. 1997.
6. S. Mukherjea, K. Hirata, and Y. Hara, “AMORE: A World Wide Web Image Retrieval Engine,” Proc. World Wide Web, vol. 2, no. 3, pp. 115-132, June. 1999.
7. A. Natsev, R. Rastogi, and K. Shim, “WALRUS: A Similarity Retrieval Algorithm for Image Databases,” IEEE Trans. On Knowledge and Data Engineering, vol.16,pp. 301-318, Mar. 2004.
8. A. Pentland, R. Picard, and S. Sclaroff , “Photobook: Content based manipulation of image databases,” International Journal of Computer Vision, vol.18, no 3,pp.233–254, June 1997.
9. R. Picard and T. Kabir, “Finding Similar Patterns in Large Image Databases,” Proc. IEEE Int. Conf. Acoustics, Speech and Signal Processing, vol. 5, pp. 161-164, New York 1993.
10. C. Carson, M. Thomas, S. Belongie, J.M. Hellerstein, and J. Malik, “Blobworld: A System for Region-Based Image Indexing and Retrieval,” Proc. Visual Information Systems, pp. 509-516, June 1999.
11. J. Smith and S. Chang, “Visualseek: A Fully Automated Content-Based Image Query System,” Proceedings of the 4th ACM international conference on Multimedia table of contents, Boston, Massachusetts, United States, Nov. 1996, pp. 87-98.
12. W. Ma and B. Manjunath, “Natra: A Toolbox for Navigating Large Image Databases,” Proc. IEEE Int'l Conf. Image Processing, Santa Barbara, 1997, pp. 568- 571.
13. J. Wang, G. Wiederhold, O. Firschein, and X. Sha, “Content-Based Image Indexing and Searching Using Daubechies' Wavelets,” Int. J. Digital Libraries, vol. 1, no. 4, pp. 311-328, 1998.
14. J. Yang, W. Lu and A. Waibel, 1998. “ Skin-color modeling and adaptation”, ACCV98.
15. S. Manimala and K. Hemachandran, “Performance analysis of Color Spaces in Image Retrieval”, Assam University Journal of science & Technology, Vol. 7, Number II 94-104, 2011.
16. Vladimir Vezhnevets, Vassili Sazonov, and Alla Andreeva,2003. “A Survey on Pixel-Based Skin Color Detection Technique”,In Proceedings of the Graphi Conference, pp.85-92.
17. P. Kakumanu, S. Makrogiannis and N. Bourbakis, 2006. “A survey of skin-color modeling and detection methods”. The journal of the pattern recognition society.
18. Dong Yin, Jia Pan, et al, "Medical Image Categorization based on Gaussian Mixture Model", IEEE 2008 International Conference on BioMedical Engineering and Informatics, pp. 128-131.
19. J.Z. Wang, “Wang Database,” [Online], Available at: http://wang.ist.psu.edu/ , last visited June 2013.
20. Y. Liu, D. Zhang, G. Lu, and W. Ma, “A survey of content based image retrieval with high-level semantics,” Journal of Pattern Recognition, vol. 40, pp. 262–282, Nov. 2007.

Published By:
Blue Eyes Intelligence Engineering
and Sciences Publication (BEIESP)