IJCAT International Journal of Computing and Technology, Volume 1, Issue 3, April 2014
ISSN : 2348 - 6090
www.IJCAT.org

A Review on Feature Extraction Techniques for CBIR

[1]Abhijeet Mallick, [2] Deepak Kapgate , [3] Nikhil Vaidya

[1] PG Scholar, CSE GHRAET, Nagpur, Maharashtra, India

[2] Professor, CSE GHRAET, Nagpur, Maharashtra, India

[3] PG Scholar, CSE GHRAET, Nagpur, Maharashtra, India

Abstract - Content Based Image Retrieval (CBIR) is becoming effective source of fast retrieval on Image database for current internet world as it contains large collections of images. Content Based Image Retrieval (CBIR) is a technique which uses visual features of image such as color, shape, texture, etc. to search user required image from large image database according to user's requests in the form of a query image. Images are retrieved on the basis of similarity in features where features of the query specification are compared with features from the image database to determine which images match similarly with given features. Feature extraction is a crucial part for any of such retrieval systems. In this paper we survey some technical aspects of current content-based image retrieval systems and the features extraction techniques like color histogram, texture, and shape is done. Also paper gives the comparative analysis of mentioned techniques with different metrics.

***Keywords* - Content-Based Image Retrieval (CBIR), Color Histogram, Texture, HSV Color and Wavelet decomposition.**

1. Introduction

The content based image retrieval system mainly design for solving the various problem like analysis of low level image feature, multidimensional indexing and data visualization. Content based image retrieval system does not depended on the additional image information such as time and place of the creation or text annotation. The content based image retrieval system is depended on the content of image. Image mainly contains visual content and the semantic contain. The visual content of image are color, shape, texture and the semantic content are complex and dependent on the visual content. Image if we deal with the human eyes the color is main part of image which we used for tlor he image reorganization and verification but if we deal with the sign of images similar images are having the same sign. So the color is not enough to retrieve images so the texture of image is also used for the image retrieval system. Semantic Feature: Also known as the high level feature like text annotation. Visual Feature: Also known as the low level feature like Color, texture and shape.

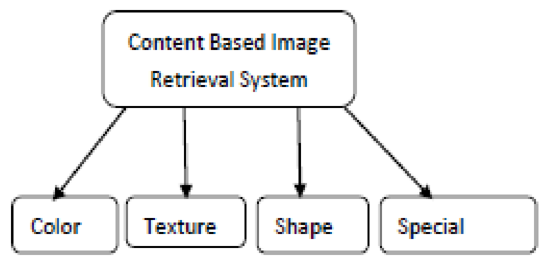

Fig 1: Techniques for content based image retrieval system

2. Color Feature

Color feature is the most important and significant feature for searching image from collection of images. The color property is one of the most widely used visual features. Color feature is the most significant one in searching collections of color images of arbitrary subject matter. Color plays very important role in the human visual perception mechanism. Besides, image color is easy-to analyze, and it is invariant with respect to the size of the image and orientation of objects on it. This explains why the color feature is most frequently used in image retrieval, as well as the fact that the number of fundamentally different approaches is not too great.

The color feature can be extracted from many methods as follow

1. Histogram method
2. Statistical method
3. Color model

2.1 Color histogram

Color Histogram can be classified into the following type

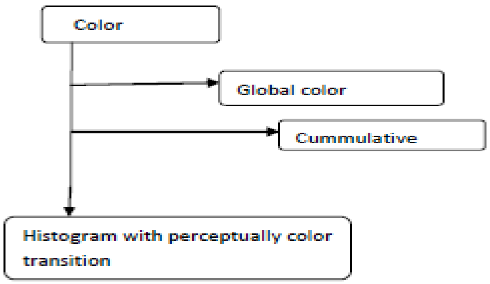

Fig 2: Color transition in histogram

Color histogram is simplest and most frequently used to represent color. The color histogram serves as an effective representation of the content. The color pattern is unique compared with the rest of data set. The color histogram is easy to compute and effective in characterizing both global and local color.

In color histogram the number of pixel of given color is calculated the color histogram extraction algorithm involves following three steps.

1) Partition of color space into cells.
2) Association of each cell to a histogram bin.
3) Counting of number of image pixel of each cell and storing this count in the perspective corresponding histogram bin.

2.2 Color Model

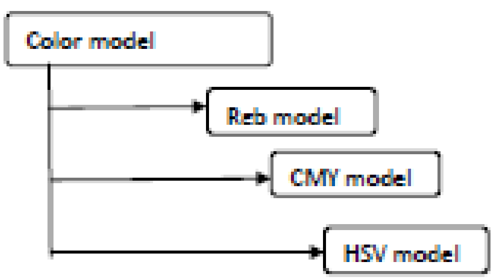

Fig 3: Types of color model

The color model and color space are also known as the color system. Subspace within the system where each color is represented by the single point .Therefore in color space each color has its color co-ordinates.

Following are some most frequently used color model.

- RGB model stands for the red green blue model which used in color monitoring and camera's
- CMY model cyan magenta and yellow or CMYK stands for cyan, magenta yellow, and Black used for color printer.
- HSV stands for Hue , Saturation value We can use the various techniques to convert from one model to another model. the RGB is most traditional space which used to representing digital image.

2.3 Statistical Model

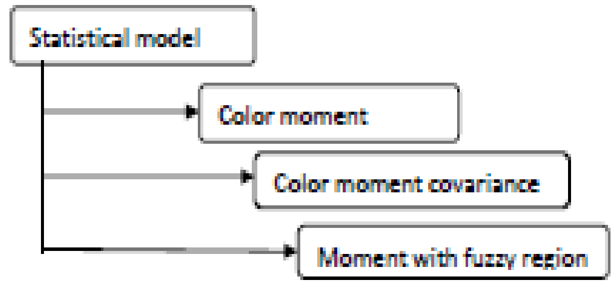

Fig 4: Techniques for statistical kodel

Statistical model is alternative to the histogram model for color representation. This model is based on probability distribution of indivisible color. The QBIC system uses the color moment.

The first order (mean)

The second order (variance)

The third order (skewness)

$$\mu i = 1/N \sum_{j=1}^{N} fij$$

$$\sigma i = \left(\frac{1}{N}\sum_{j=1}^{N} (fij - \mu i)^{2}\right)^{1/2}$$

$$Si = \left(1/N \sum_{j=1}^{N} (fij - \mu i)^{3}\right)^{1/3}$$

Where f_{ij} is the value of the i^{th} color component of image pixel j and N is the number of pixel in the image. Generally the color moment is used as the first filter to cut down the search space before other color feature used for the retrieval.

3. Texture Feature

Similar to color feature the texture feature is also important for the image retrieval. The texture gives us information on the structural arrangement of surface and object on the image. Texture characterized by the basic primitives whose spatial distribution creates some visual pattern defined in term of granularity, directionality and repetitiveness.

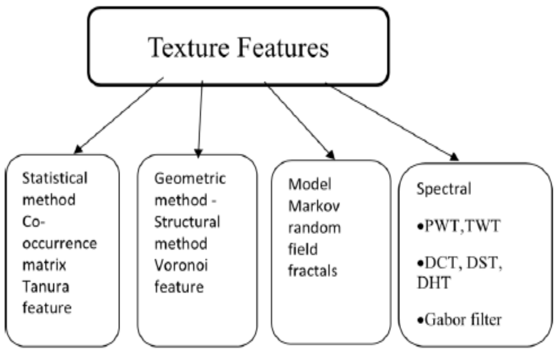

Fig 5: Types of texture extraction feature

3.1 Statistical Feature

The most frequently used statistical feature include

- General statistical parameter calculated from pixel intensity values.
- Parameter calculated based on co-occurrences matrix
- Texture histogram build upon Tanura feature

Tanura feature It contains set of visual feature. The set is coarseness, contrast, directionality, regularity, roughness.

Coarseness: is measure of granularity of texture.

Contrast: It measures how gray level varies in image and what extend their distribution towards black or white.

Directionality: is measure the frequency distribution of oriented local edge against their directional angle.

Regularity: it defines as F_{reg} =1-r(S_{cr}s+S_{con}+S_{dir}+Sl_{im}) where r is normalizing factor and each S.

Roughness: Is summation of coarsness and contrast measure.

$F_{rgh}= F_{crs} + F_{com}$

Co-Occurrence matrix

The co-occurrence matrix is also known as gray level co-occurrences matrix. This is first method of Texture feature. The co-occurrence matrix is defined as frequency matrix of pair of pixels of certain intensity levels with respect to one another.

Let consider the image I of size N*M, then Co-occurrences matrix defined as

$C(I,j)=\Sigma^{N}_{p=1}\Sigma^{M}_{q=1}\{$ 1 , if I(p,q)=i

I(p+Δx,q+Δy)=j

O, otherwise. $\}$

3.2 Spectral Method

The spectral approach for texture analysis deals with images in the frequency domain hence this methods requires Fourier transformation to be carried out on the original images to acquire their corresponding representations in the frequency space. The 2-D power spectrum of an image reveals much about the periodically and directionality of its texture. An image of coarse texture would have a tenancy towards low frequency components in its power spectrum, whereas another image with finer texture would have higher frequency components for instance. Stripes in one direction would cause the power spectrum to concentrate near the line through the origin and perpendicular to the direction.

3.3 Gabor Filters

Gabor filters transform is a good multi resolution approach which represents the texture of an image. It is an effective way using multiple orientations and scales. The 2-D Gabor function can be specified by the frequency of the sinusoid *W* and the standard deviation *σx* and *σy*, of the Gaussian envelope as:

$$g(x,y) = \frac{1}{\sigma_x\sigma_y}\exp(-\frac{1}{2}\left(\frac{x^2}{\sigma^2{}_x}+\frac{y^2}{\sigma^2{}_y}\right)+2\pi jW_x$$

3.4 Wavelet-Based Texture Description

Region-based image retrieval was proposed to extend content-based image retrieval so that it can cope with the cases in which users want to retrieve images based on information about their regions. The region-based systems which use wavelet transform are classified into three categories: a hierarchical block, a moving window and a pixel. Since these methods are subject to some limitations, several improvements have been proposed. Then the texture features are calculated from wavelet coefficients of all regions (sub bands).

The segmented regions are indexed by the averaged features in the regions. After decomposing the image into non[100]. Wavelet analysis performs decomposition of signals in terms of a special basis. The basis wavelet functions are constructed from one mother wavelet function obtained by performing translation and scaling operations. The best result was achieved for the wavelet.

Approach and homogeneous decomposition, accuracy of such results was greater than 90%. This wavelet transform is known as *pyramidal* wavelet transforms (PWT). But this technique has one disadvantage that frequency bands obtained are in logarithmic relation. However, this difficulty can be overcome by using *tree-structured wavelet transform* (TWT) in which extension of the wavelet transform that is *wavelet packages*. This method is suggested in 1992 by Coifman and Wickerhauser [34]. Results of experiments on comparison of efficiencies of various transformations for obtaining texture features is presented in Chang and Kuo[16].

4. Conclusion

It is concluded that a wide variety of CBIR algorithms have been proposed in different papers. The selection feature is one of the important aspects of Image Retrieval System to better capture user's intention. It will display the images from database which are the more interest to the user. The purpose of this survey is to provide an overview of the functionality of content based image retrieval systems. The color moment have the highest precision to extract for color feature and Gabor filter have highest precision for texture feature detection. Future work may include development of CBIR system for multimedia application.

References

[1] Rui, Y., Huang, T.S., and Chang, S.-F., Past, Present and Future, *Proc. of Int. Symp. on Multimedia Information Processing*, 1997.

[2] Black, K.K., Fahmy, G., Kuchi, P., and Panchanathan, S., Characterizing the High-Level Content of Natural Images Using Lexical Basis Functions, *Proc. Of Human Vision and Electronic Imaging Conf. SPIE 2003*, Santa Clara, 2003.

[3] Vassilieva, N., Dol'nik, A., and Markov, I., Image Retrieval. Synthesis of Different Retrieval Methods in Result Formation. Internet-mathematics 2007, *Sbornik rabot uchastnikov konkursa*, (Collection of Papers of Competition Participants), Ekaterinburg: Ural'skii Universitet,2007.

[4] Safar, M., Shahabi, C., and Sun, X., Image Retrieval by Shape: A Comparative Study, *Proc. of the IEEE Int. Conf. on Multimedia and Expo*, 2000, vol. 1, pp. 141–144.

[5] Grosky, W. and Stanchev, P., An Image Data Model, *Proc. of Advances in Visual Information Systems: The 4th Int. Conf., VISUAL 2000*, Lyon, France, 2000, pp. 227–243.

[6] Gonzalez, R.C. and Woods, R.E., *Digital Image Processing*, Prentice Hall, 2002. [7]Color space. *Wikipedia, The Free Encyclopedia.* http://en.wikipedia.org/wiki/Color_space.

[7] Chitkara, V., Color-Based Image Retrieval Using Compact Binary Signatures, *Tech. Report TR 01-08*, University of Alberta Edmonton, Alberta, Canada, 2001.

[8] Stricker, M. and Orengo, M., Similarity of Color Images, *Proc. of the SPIE Conf.*, 1995, vol. 2420, pp. 381–392.

[9] Swain, M.J. and Ballard, D.H., Color Indexing, *Int. J. Computer Vision*, 1991, vol. 7, no 1, pp. 11–32.

[10] Niblack, W., Barber, R., et al., The QBIC Project: Querying Images by Content Using Color, Texture and Shape, *Proc. of IS & T/SPIE Int. Symp. on Electronic Imaging: Science & Technology*, 1993, vol. 1908: Storage and Retrieval for Image and Video Databases.

[11] Smith, J.R. and Chang, S.-F., Single Color Extraction and Image Query, *Proc. of the IEEE Int. Conf. on Image Processing*, 1995.

[12] Smith, J.R. and Chang, S.-F., Tools and Techniques for Color Image Retrieval, *Proc. of IS & T/SPIE*, vol. 2670. Storage & Retrieval for Image and Video Databases IV, 1995.

[13] Ioka, M., A Method of Defining the Similarity of Images on the Basis of Color Information, *Tech. Report RT-0030*, IBM Tokyo Research Lab, 1989.

[14] Vassilieva, N. and Novikov, B., Construction of Correspondences between Low-level Characteristics and Semantics of Static Images, *Proc. of the 7th All-Russian Scientific Conf. "Electronic Libraries: Perspective Methods and Technologies, Electronic Collections" RCDL'2005*, Yaroslavl', Russia, 2005.

[15] Coifman, R.R. and Wickerhauser, M.V., Entropy-based Algorithms for Best Basis Selection, *IEEE Trans. Information Theory*, 1992, vol. 38, no. 2, pp. 713–718.

[16] Tianhorng, C. and Kuo Jay, C.-C., Texture Analysis and Classification with Tree-structured Wavelet Transform, *IEEE Trans. Image Processing*, 1993, vol. 2, no. 4, pp. 429–441.

[17] Thyagarajan, K.S., Nguyen, T., and Persons, C.E., A Maximum Likelihood Approach to Texture Classification Using Wavelet Transform, *Proc. of the IEEE Int. Conf. on Image Processing ICIP-94,* 1994, vol. 2, pp. 640–644.

[18] Balmelli, L. and Mojsilovic, A., Wavelet Domain Features for Texture Description, Classification and Replicability Analysis, *Wavelets in Signal and Image Analysis: From Theory to Practice*, Petrosian, A.A., Meyer, F., Eds., Kluwer Academic, 2001.

[19] Kingsbury, N., Image Processing with Complex Wavelets, *Phil Transactions of Royal Society of London*, A, 1999, vol. 357 (1760), pp. 2543.

[20] Do, M.N. and Vetterli, M., Texture Similarity Measurement Using Kullback–Leibler Distance on Wavelet Subbands, *Proc. of Int. Conf. on Image Processing*, 2000, vol. 3, pp. 730–733.

[21] Sebe, N. and Lew, M.S., Wavelet Based Texture Classification,*Proc. of Int. Conf. on Pattern Recognition*, 2000, vol. 3, pp. 959–962.

[22] Manjunath, B.S. and Ma, W.Y., Texture Features for Browsing and Retrieval of Image Data, *IEEE Trans. Pattern Analysis Machine Intelligence*, 1996, vol. 18, no. 8, pp. 837–842.

[23] Manjunath, B.S., Wu, P., Newsam, S., and Shin, H.D.,A Texture Descriptor for Browsing and Similarity Retrieval, *Proc. Signal Processing Image Commun.,* 2000, nos. 1–2, pp. 33–43.

[24] Ma, W.Y. and Manjunath, B.S., Texture Features and Learning Similarity, *Proc. of the 1996 Conf. on*

ISSN : 2348 - 6090
www.IJCAT.org

Computer Vision and Pattern Recognition (CVPR'96), 1996, p. 425.

[25] Bell, A.J. and Sejnowsky, T.J., The ―Independent Components‖ of Natural Scenes are Edge Filters, *Vision Research,* 1997, no. 37, pp. 3327–3338.

[26] Borgne, H., Guerin-Dugue, A., and Antoniadis, A., Representation of Images for Classification with Independent Features, *Pattern Recognition Letters*, 2004, vol. 25, pp. 141– 154.

[27] Snitkowska, E. and Kasprzak, W., Independent Component Analysis of Textures in Angiography Images, *Computational Imaging Vision*, 2006, vol. 32, pp. 367–372.