IJCSE International Journal of Computer Sciences and Engineering Open Access
Review Paper Volume-4, Issue-3 E-ISSN: 2347-2693

Review of Content Based Image Retrieval Using Low Level Features

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www.ijcseonline.org

Received: Feb/24/2016 Revised: Mar/03/2016 Accepted: Mar/19/2016 Published: Mar/31/ 2016

Abstract- Content based image retrieval is a important research area in the field of image processing used for searching and retrieving images from large database. It uses virtual content of images comprises of low level feature extraction such as color, texture, shape & spatial locations to represent images in the database. The system retrieves similar images images when an example image or sketch is presented as input to the system. This paper provides review of the approaches used for extracting low level features, various distance measures for retrieval, various datasets used in CBIR & performance measures. Creation of a content-based image retrieval system implies solving a number of difficult problems, including analysis of low-level image features and construction of feature vectors, multidimensional indexing, design of user interface, and data visualization. Quality of a retrieval system depends, first of all, on the feature vectors used, which describe image content. The paper presents a survey of common feature extraction and representation techniques and metrics of the corresponding feature spaces. Color, texture, and shape features are considered.

Keywords- Content based image retrieval (CBIR), Image retrieval, and feature extraction

I. INTRODUCTION

With the advancement in internet and multimedia technologies, a huge amount of multimedia data in the form of audio, video and images has been used in many fields like architecture design , archaeology , medical imaging and geographic info system , trademark databases, criminal investigations , image search over the Internet .Nowadays for retrieving the images from large resources visual features like color, texture & shape are implemented. Basically image retrieval is a two step process where features are extracted in the first step & in second step matching of features is done with query image features.

A. Origin of the Research Problem:

There are many large resources available on the web sites to create and store images. Therefore it is necessary to mechanism to manage and search these images. For the last few decades, researchers have been working on image retrieval processes to find efficient image retrieval mechanism and they developed two types of image retrieval techniques such as, text based image retrieval and content based image retrieval (CBIR).

In text based image retrieval method, users use keyword or description to the images as query so that they can use the retrieved images, which are relevant to the keyword. Text based retrieval has several disadvantages. First of all, there is inconsistency in labeling by different annotators due to different understanding about image contents. Second, it consumes a lot of time to annotate each image in a large database and makes the process subjective. Third, there is a high probability of error occurrence during the image tagging process when the database is large. As a result, text based image retrieval cannot achieve high level of efficiency and effectiveness. Yahoo web based image searching is an example which uses text based image retrieval. In most cases, we find only the first few retrieved images are relevant to the query.

Some representatives of CBIR system are Query By Image Content (QBIC)[Flicker Simplicity[Wang and Blob world[Carson]. The term CBIR originated in the early 1990's. It is an automated technique that takes an image as query and returns a set of images similar to the query. Low-level image features like texture, color, and shape are extracted from the images of the database to define them in terms of their features. Images of the same category are expected to have similar characteristics. Therefore, when similarity measurement is performed on the basis of image features, the output set achieves a high level of retrieval performance. CBIR has several advantages over the traditional text based retrieval. Due to using the visual contents of the query image in CBIR, it is a more efficient and effective way at finding relevant images than searching based on text annotations. Also CBIR does not consume the time wasted in manual annotation process of text based approach. These advantages motivate to employ a CBIR technique for study.

B. Objective of the study:

The objective of the study is
->To improve existing techniques involved in feature extraction, similarity matching.

->To reduce the overall computation time of image retrieval system while increasing the accuracy.

II. METHODOLOGY:

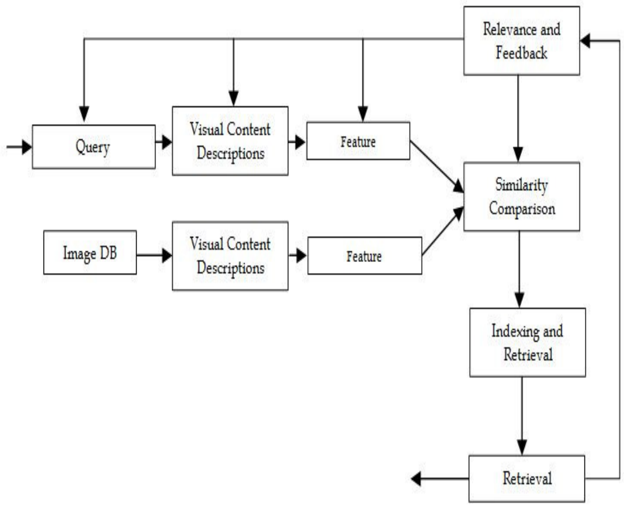

Figure1: Diagram for content based image retrieval system

In a typical CBIR system (Figure 1), the low level features of images in the database are extracted to form a feature database. The retrieval process is initiated when a user query the system using an example image or sketch of the object. The low level features of query image are also extracted using the same feature extraction routine that was used for building the feature database. The similarity measure is done to calculate the distance between the feature vectors of query image and that of the images in the feature database. Finally, the retrieval is performed using an indexing scheme which facilitates the efficient searching of the image database. Recently, user's relevance feedback is also incorporated to further improve the retrieval process in order to produce perceptually and semantically more meaningful retrieval results.

A. Visual Content Descriptor

Natural images depicting a complex scene may contain a variety of visual artifacts. CBIR systems represent the visual contents of images in the form of a feature descriptor. A good descriptor should not only be invariant to rotation, scaling and illumination variations but also has high discriminating capability. However, there is a tradeoff between invariance and discriminating power of visual features. Employing features having wide variety of invariance may result in losing the capability to discriminate between most essential properties. Study of invariance is largely investigated in the field of computer vision.

A feature descriptor may be local or global. Local descriptors are extracted using a part or region of an image while a global feature uses the visual content of the whole image. A CBIR system which uses region features to represent images is known as Region Based Image Retrieval systems (RBIR). On the other hand CBIR systems utilizing global features for describing images are classified as Global CBIR systems. Local and Global features of an image largely represent color, texture, shape and spatial relationships of different objects in the image. Some widely used color, texture, shape and spatial relationship features are discussed in the following subsections.

a)Color Features

Color is the most commonly used feature of an image. The perceived color at any pixel of an image is obtained by mixing three preliminary colors in appropriate proportion. The three dimensional color provides more discriminating information than the single dimensional gray level values. Before extracting color descriptor a proper color space must be determined first. Commonly used color spaces for image retrieval application are RGB, CIE L*a*b*, CIE L*u*v*, HSV and opponent color space. There is no agreement over which color space is best but one of the desirable characteristic of color space for image retrieval task is its uniformity. Uniformity means that the physical distance between any two color pair in the color space must be equal to the perceived distance between them. Color moments, color histogram, color coherence vector and color correlogram [2-6] are the commonly used color descriptors.

b)Texture Features

There is no specific definition of texture however one can define texture as the visual pattern that has properties of homogeneity not resulting from the presence of only a single color or intensity. Various techniques for texture analysis have been investigated in the field of computer vision and pattern recognition. The texture extraction techniques can be classified into two categories: statistical and structural. Statistical approaches use intensity distribution of image to extract statistical parameters representing texture of image. Commonly used statistical methods include Fourier power spectra, Co-occurrence matrices, Shift-invariant principal component analysis (SPCA), Tamura feature, Wold decomposition, Markov random field, Fractal model, and Multi-resolution filtering techniques such as Gabor and wavelet transform. Structural methods, including morphological operator and adjacency graph, describe texture by identifying structural primitives and their placement rules. When applied to textures that are very regular they tend to be most effective.

Among the low level image features, texture has been shown to be effective in CBIR. The techniques for extracting texture features are broadly classified into the spatial and spectral methods. In spatial approach on statistical calculations on the image are done. The main disadvantages of statistic techniques are sensitive to image noise and have insufficient number of features. On the other hand, spectral methods of texture analysis for image retrieval are robust to noise. The spectral methods include the use of discrete cosine transform, multiresolution (MR) methods such as, Gabor filters and wavelet transform for texture representation. We have to find better multiresolution spectral approaches, which can capture the edge and orientation information of an image effectively because r discrete cosine transform, multiresolution (MR) methods such as, Gabor filters and wavelet transform for texture representation do not capture the edge & orientation information of an image effectively.

c) Shape Features

Shape feature provides the most important semantic information about an image. Shape features are usually described using part or region of an image. The accuracy of shape features largely depends upon the segmentation scheme used to divide an image into meaningful objects. However, fast and robust segmentation is difficult to achieve. This limits the shape features only to those retrieval applications where objects or region of images are readily available. The shape descriptors are categorized into two classes: boundary based descriptor and region based descriptor. Some boundary based representative shape description techniques are chain codes, polygonal approximations, Fourier descriptor and finite element model. On the other hand state of the art region based descriptors are statistical moment and area. The main requirement of good shape feature is that they should be invariant to translation, rotation and scaling.

d)Partial Information

The performance of a image retrieval system can be improved by considering spatial locations of different objects in the image. The spatial location of objects and their relationship can provide useful discriminating information in image retrieval applications. For example blue sky and ocean may have similar color histograms, but in images their spatial locations are different. The spatial location matching can be implemented by matching the images based on fixed location similarity. In this approach a similar object lying in different regions of an image cannot be detected. For instance; image having tiger in the left part may not get similarity with images having tiger in the right part of images. To overcome this problem systems compare all region of image with the query object or region. This may result in the increase of response time of the system. The most commonly used techniques for finding spatial location similarity includes 2D strings, spatial quad-tree and symbolic images.

III. SIMILARITY MEASURE

The degree of similarity between query and target images is calculated based on the value of similarity measure. The images are ranked according to their similarity value and presented as output of CBIR system. Often, the choice of similarity measure affects the performance of retrieval system. Many similarity measures have been developed over the years based on the quantitative estimates of the distribution of features in the image. Different similarity matching techniques are used by different researchers. Some of the most commonly used similarity measures employed in CBIR are

i) Euclidean distance
ii) Minkowski- form distance,
ii) Histogram intersection distance,
iii) Quadratic- form distance,
iv) Mahalanobis distance and
v) Kullback Leibler (KL) divergence distance.

IV. PERFORMANCE EVALUATION-

The performance of a retrieval system is evaluated based on several criteria. Some of the commonly used performance measures are average precision, average recall, average retrieval rate and Average Normalized Modified Retrieval Rate (ANMRR). All these parameter are computed using precision and recall values computed for each query image.

Precision is the ratio of the number of relevant images you have retrieved to the total number of irrelevant and relevant images retrieved. In other words, supposing that A was the number of relevant images retrieved and B was the total number of irrelevant images retrieved. When calculating precision, you take a look at the first several images, and this amount is A + B, as the total number of relevant and irrelevant images is how many images you are considering at this point.

Precision= No. of relevant images retrieved/ Total no . of images retrieved from the database

Precision = A / (A + B)

The definition of Recall is slightly different. This evaluates how many of the relevant images you have retrieved so far **out of a known total**, which is the the total number of relevant images that exist. Supposing that A was again the total number of relevant images you have retrieved out of a bunch you have grabbed from the database and C represents the **total** number of relevant images in your database.

$$\text{Recall}= \frac{\text{No. of relevant images retrieved}}{\text{Total no. of relevant images in the database}}$$

Recall = A / C

Precision-Recall graphs measure the accuracy of your image retrieval system. A good retrieval system should have high values for precision and recall. Generally, a tradeoff must be made between these two measures since improving one will sacrifice the other. In typical retrieval systems, recall tends to increase as the number of retrieved items increases; while at the same time the precision is likely to decrease. Also selecting a relevant data base is much less stable due to various interpretations of the images. Recall is meaningless when the number of relevant images is greater than the number of the retrieved images.

V. COMPARISION OF WORK ON CBIR

Title & Authors	Journal &Year	Methods used	Database	Features Extracted	Similarity Measure	Performance
Content based retinal image retrieval using dual tree complex wavelet transform [Christina George Bab, D.Abraham Chandy]	International Conference on Signal processing ,Image Processing and Pattern Recognition [ICSIPR], 2013	The combination of two dimensional dual-tree complex wavelet transform (DT -CWT) and generalized Gaussian density (GGD) model	MESSIDOR dataset.	The feature comprises the GGD model parameters of each level detail coefficients and the highest level approximation coefficients	Kulback-Leibler divergence (KLD)	Mean precision rates
Colour and texture feature-based image retrieval by using Hadamard matrix in discrete wavelet transform [Hassan Farsi, Sajad Mohamadzadeh]	IET Image Process. 2013, Vol. 7, Iss. 3, pp. 212–218 doi: 10.1049/iet-ipr.2012.0203, 2013	Combination of Hadamard matrix and discrete wavelet transform (HDWT) in hue-min-max-difference colour space.	(i) Corel dataset (ii) The Amsterdam Library of Object images (ALOIs) dataset (iii) MPEG-7 dataset	Color & texture	Euclidean distance	An average normalized rank and combination of precision and recall.
Content Based Image Retrieval using Discrete Wavelet Transform and Edge Histogram Descriptor [Swati Agarwal, A. K. Verma, Preetvanti Singh]	International Conference on Information Systems and Computer Networks IEEE,2013	Wavelet Transform, Edge Histogram Descriptor	Wang Database	Texture and shape based features	Manhattan Distance	Precision & recall
An Effective CBIR (Content Based Image Retrieval) Approach Using Ripplet Transforms [Nivya Sasheendran, C. Bhuvaneswari]	International Conference on Circuits, Power and Computing Technologies [ICCPCT-2013]	Ripplet Transform (RT) along with the Neural network based classifier called Multilayered perceptron(MLP)	WANG database	Texture and color	Manhattan Distance	precision-recall
Image Retrieval System Based on Wavelet network [Hamid Jalab,Alim Hasan]	IEEE,2012	Wavelet Network	The proposed CBIR method is tested using an image database database with 1,000 images spread across 10 classes containing 100 images each; images in the same class are considered similar images.	Texture features	-----	Average precision and recall. The efficiency is reached upto 63%.
A comparative Study Of Different Transformation Techniques For CBIR [Syed Akhter Hussain, Prof. A.N.Holambe, Zeeshan Shaikh]	(IJERT) Vol. 1 Issue 8, ISSN: 2278-0181, 2012	DCT, DWT, LBP and discrete curvelet transform	Different type of hundred images were collected and stored as the database	Mean, Standard Deviation	Distance	Precision recall &Efficiency

Row, Column and Fused Row-Col R, G, B Plane's Feature Vector Generation using DCT, DST and Kekre Wavelet for CBIR [Dr. H. B. Kekre, Kavita Sonawane]	IEEE, International Conference on Communication, Information & Computing Technology (ICCICT), Oct. 19-20, Mumbai, India, 2012	DCT, DST, Kekre Wavelet	Database of 1000 BMP images to demonstrate the work done in this paper. It has 10 classes where each class includes 100 images of its own category. The 10 image classes used are Flower, Sunset, Mountain, Building, Bus, Dinosaur, Elephant, Barbie, Mickey, Horse.	Using DCT, DST and Kekre wavelet transforms over row and column mean vectors of R, G and B planes of images to form the feature vectors the color and texture information	Absolute distance, Euclidean distance,	Performance of the system is evaluated using two parameters 'Precision Recall Cross Over Point (PRCP)', and 'Longest String
Content-based image retrieval using the combination of the fast wavelet transformation and the colour histogram [M. Singha, K. Hemachandran, A. Paul]	IET Image Process., 2012, Vol. 6, Iss. 9, pp. 1221–1226 doi: 10.1049/iet-ipr.2011.0453	Haar wavelet transformation using lifting scheme and the colour histogram (CH) called lifting wavelet-based colour histogram	WANG database containing 1000 images of the Corel stock photo database, in JPEG format of size 384 × 256 and 256 × 386.	Color & texture	Histogram intersection for colour image retrieval.	Precision, recall
Content-Based Image Retrieval for Interstitial Lung Diseases [Jatindra Kumar Dash, Rahul Das Gupta, Sudipta Mukhopadhyay, Niranjan Khandelwal, Pinakpani Bhattacharya, Mandeep Garg]	IEEE,2012	Discrete Wavelet Transform (DWT), Dual Tree Complex Wavelet Transform (DTCWT) and DT-CWT combined with Dual Tree Rotated Complex Wavelet Frame (DT-RCWF)	The dataset used for evaluation contains 64 images representing four Interstitial Lung Diseases ILDs pattern such as consolidation, nodular, emphysema, ground glass and normal	Rotation invariant texture feature, energy and standard deviation of each decomposed sub bands	City-block distance	Precision and recall
Interactive Content-Based Texture Image Retrieval [Pushpa B. Patil, Manesh B. Kokare]	International Conference on Computer & Communication Technology (ICCCT)-2011, 978-1-4577-1386-611, IEEE 2011	Dual Tree Complex Wavelet Transform (DT-CWT);DT-RCWT, Contourlet Transform and Curvelet Transform	108 textures from Brodatz texture photographic album, seven textures from USC database and one artificial texture (116). Size of each texture image is 512x512.	Texture	Canberra distance	Average accuracy.
Localised functional neuroimaging retrieval using 3D discrete curvelet transform [Sidog Liu,Weidog cai ,Lingfeng Wen, Stefan Eberl, Michael J Fulham,Dagan Feng]	978-1-4244-4128-0/11/IEEE, 2011	3D digital curvelet transform	A neuro-informatics database system (NIDS) with co-registered static PET and MR image data for temporal lobe epilepsy studies built by Wong et al.	Multiscale Texture Feature Extraction	Euclidian distance	Average precision
Significant region based image retrieval using curvelet transform [P. Manipoochelvi,	978-1-4577-2149-6/11/IEEE, 2011	Curvelet Transform in combination with color histogram	Coral database of about 1000 images	Texture & color	Euclidean distance	Precision, recall &_measure

K.Muneeswaran]						
Combined feature descriptor for content based image retrieval [S. Selvarajah and S. R. Kodithuwakku]	2011	2D Discrete Wavelet Transform, Haar wavelet, colour histogram	A general purpose image database consists of 1000 images	Colour and texture features, combined	Histogram colour moments, Sum-of-Absolute Differences (SAD) method is used.	Average Precision
A Texture-Based Approach for Content Based Image Retrieval System for Plant Leaves Images [Ahmed Naser Hussein, Syamsiah Mashohor, M. Iqbal Saripan]	IEEE 7th International Colloquium on Signal Processing and its Applications, 978-1-61284-413-8/11/$26.00 ©2011 IEEE	Discrete wavelet Transformation	American National Herbarium Collections database	Texture	Entropy, Euclidian distance	Correctness retrieval rate
Image Retrieval with Rotation Invariance [P.N.R.L.Chandra Sekhar, P. Surya Prasad, M.Vinodh Kumar, D. Hari Hara Santosh]	978-1-4244-8679-3/11/$26.00 ©2011 IEEE	Rotation invariant CBIR by using Curvelet texture feature	1000 images are taken from the COREL data set which consists of 10 different categories and each contains 100 varieties of images.	Color & texture	Mean and standard deviation, Euclidian distance	Precision recall
Combining Color Quantization with Curvelet Transform for Image Retrieval [Yungang Zhang, Lijing Gao, Wei Gao and Jun Liu]	2010 International Conference on Artificial Intelligence and Computational Intelligence, 978-0-7695-4225-6/10 $26.00 © 2010 IEEE, DOI 10.1109/AICI.2010.105	Color histogram; curvelet transform;	Image database has 565 images, the images in the database are in 20 categories, such like flower, mountain, sea, tree, football, building etc. Every category has about 30 images	Color and shape	Manhattan distance	Precision
Curvelet texture based face recognition using PCA [Shafin Rahman, Sheikh Motahar Naim, Abdullah Al Farooq and Md. Monirul Islam]	Proceedings of 13th International Conference on Computer and Information Technology (ICCIT 2010) 23-25 December, 2010, Dhaka, Bangladesh, 978-1-4244-8494-2/10/$26.00 ©2010 IEEE	Curvelet transform	Face databases-Yale, ORL , and Faces94 face Databases	Texture feature, mean & standard deviation	Principal component Analysis classifier	Recognition rate
Content Based Image Retrieval Based on BEMD: use of Curvelet Transform coefficients distribution and Gabor wavelets [M. H. Ould Mohamed Dyla, H.Tairi, A.Aarab]	978-1-61284-732-0/11/$26.00 ©2010 IEEE	Curvelet Transform; Gabor Wavelets	Brodatz database	By using global information extracted from the image Bidimensional Empirical Mode Decomposition (BEMD) Images are characterized	Texture	Precision recall
CT Image Retrieval Using Tree Structured Cosine Modulated Wavelet Transform [Manesh Kokare]	International Conference on Digital Image Processing, 978-0-7695-3565-4/09 $25.00 © 2009 IEEE, DOI 10.1109/ICDIP.2009.63	Standard wavelet & tree structured cosine modulated wavelet transform (TSCMWT)	640 different CT images	Texture features(Energy and Standard Deviation)	Canberra Distance	Retrieval Accuracy

Rotation invariant curvelet features for texture image retrieval [Md Monirul Islam, Dengsheng Zhang, and Guojun Lu]	978-1-4244-4291-1/09/$25.00 ©2009 IEEE, ICME 2009	Curvelet transform	Brodatz texture database which consists of 112 images of size 640 by 640 pixels	Rotation invariant curvelet feature, Energy distribution	L2 distance measure	Precision, Recall
Content Based Image Retrieval Using Curvelet Transform [Ishrat Jahan Sumana, Md. Monirul Islam, Dengsheng Zhang and Guojun Lu]	978-1-4244-2295-1/08/$25.00 © 2008 IEEE, MMSP 2008	Curvelet Transform	Brodatz texture database	Texture feature(mean and standard deviation are computed as the texture features for the curvelet)	L2 distance	Precision, recall

VI. CONCLUSION

The purpose of this review is to provide an overview of the functionality of content based image retrieval systems. This system has overcome all disadvantages of text based retrieval system. From the study it is seen that combined features can give better performance than the single feature.

VII. FUTURE SCOPE

Although for efficient searching of images content-based retrieval provides an intelligent and automatic solution, the majority of current techniques are based on low level features. These low level features tend to capture only one aspect of an image property. Neither a single feature nor a combination of multiple features has explicit semantic meaning. As the similarity measures between visual features do not necessarily match human perception. Users are interested in are semantically and perceptually similar images, the retrieval results of low-level feature based retrieval approaches are generally unsatisfactory and often unpredictable. Although relevance feedback provides a way of filling the gap between semantic searching and low-level data processing, this problem remains unsolved and more research is required.

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