International Journal of Communication Systems and Network Technologies
Vol.5, No.1, 2016

Performance Measurement Of CBIR Systems Based on different Techniques and Global Features

Kratika Sharma
Dept. of Comp. Sci. and IT
Madhav Institute of Technology and Science, Gwalior, India
kratika.it01@gmail.com

Sanjeev Jain
Dept. of Comp. Sci. and IT
Madhav Institute of Technology and Science, Gwalior, India
dr_sanjeevjain@yahoo.com

Abstract—Because of the enormous increase in graphic information, there is a need of an efficient retrieval of images arises in this information era. Content based image retrieval (CBIR) is a method that searches similar images from a large database against a query image submitted by user. Indexing, retrieving, browsing, these are the fundamental steps involved in any image retrieval system. In Content based image retrieval system (CBIR), first features are extracted from available images in the database and later stored in the feature descriptor then same features are extracted from the input query image. Images which are similar they are retrieved. This paper presents a survey on various CBIR systems and different techniques and features which are used in these contents based image retrieval systems.

Keywords—*CBIR, precision, Recall, Feature Descriptor, color, texture.*

I. Introduction

The development in digital photography, storing capacity of storage devices and bandwidth of network made it possible to store high quality large amount of images. Applications of digital images include military, medical, virtual museums and individual photograph collections.While it comes to traditional image retrieval systems, they are based on, key-words, notations, indexing icons and file names. These features become troublesome and highly time consuming, when they are used for large scale image databases and sometimes fail to describe image contents adequately. However, users have experienced inconvenience in searching huge numbers of images in the databases, as the present commercial database systems are designed for text document and not suitable for the digital images. Earlier in the case of text based retrieval systems, schemes utilized keywords for image retrieval. Therefore, an effective way for image retrieval is desired. CBIR is the research area concerned with the designing a system that can perform a search that uses image visual contents rather than text keywords instead [2]. The exponential development in image databases scale and the growth attained in Pattern Recognition covered the way of development for numerous CBIR applications, for example, in medical imaging, copyright protection, analysis of cultural heritage, trademark retrieval, SBIR, query spotting in the document images, etc. In order to increase performance of CBIR systems, EA have been used. Particularly, GA and PSO have been explored to create CBIR system adaptive to the image classes they use and to permit an extremely semantic retrieval. There are different methods for feature extraction are available for CBIR [3]. Two approaches are there, the local and global descriptors for feature extraction of an image. In global descriptor, the whole image is used for extraction of features. In local descriptor, the image is divided into different number of blocks and then the feature extraction technique is used on that block. SIMPLIcity and IBM QBIC are some of the local feature extraction based system. There are various methods to highlight extraction and likeness estimation. To improve the searching process of CBIR, classification and clustering techniques are used in feature database. Clustering is unsupervised classification technique used to form the clusters of data. Cluster is nothing but a group of similar objects and dissimilar objects are placed in different cluster. The main aim of clustering is to maximize the intra-cluster similarity and minimize the inter cluster similarity. Partitioned and Hierarchical clustering algorithms are mostly used in CBIR. CBIR system performance is improved by utilizing grouping procedures.

Preprocessing is an important step in CBIR which involves filtering, segmentation and normalization and can also be classified into 2 different stages:

1. Feature extraction: The term feature refers to an element of one or more estimations, each of which determines some quantifiable property of an article. In general, they can be categorized as general features and global features. Color, texture and shape are application independent features.
2. Similarity Measure: Similarity measures are used to estimate the similarity between images in the database and the query image and they are ranked, in order to retrieve those images first which are highly similar [4].

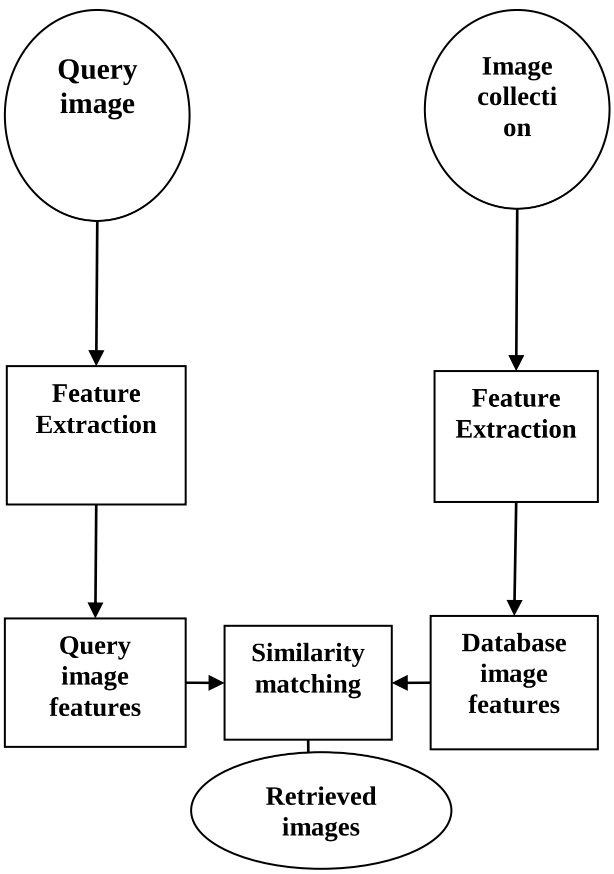

Figure 1: Block diagram of Content Based Image Retrieval

II. Color Quantization

Three channels are contained by RGB color images, representing red (R), green (G) and blue (B) colors. In the RGB color space, the range of shades lies [0, I − 1], where I denotes various distinguished shades in all channels. Considering each color for description of features is not feasible because descriptor dimension should be minimal as much as possible. We quantize RGB color space for example, it becomes a single channel of various shades. To decrease the computation complexity, RGB color space is quantized into $q \times q \times q = q^3$ bins with all colors quantized into q bins, where $q \ll l$. To retain equal weighting of all colors, each color components are quantized. The steps included in the quantisation are as follows: (1) Divide all red, green and blue image I component into q shades from I shades. The decrease color components (i.e. R_{red}, G_{red} and B_{red}) are computed as

$$Rred = \left\lceil \frac{R+1}{stp} \right\rceil \quad (1)$$

$$Gred = \left\lceil \frac{G+1}{stp} \right\rceil \quad (2)$$

$$Bred = \left\lceil \frac{B+1}{stp} \right\rceil \quad (3)$$

(2) Combine each three basic components R_{red}, G_{green} and B_{blue} into a 1-D to create the decrease color image I_{red} as follows

$$I_{red} = q^2(R_{red} - 1) + q(G_{red} - 1) + B_{red} \quad (4)$$

We quantize all RGB image colors into various shades which retains symmetric knowledge. Liu et al. Also quantized RGB color space into 64 shades, whereas Liu et al. [5] and Wang quantized HSV color space into 72 shades and quantized L*a*b* color space into 90 shades. In this paper, the value of q is chosen as 4 which leads to the 64 number of distinct shades after the quantization.

III. Feature extraction

The image X is decomposed into four various sub-bands (viz. LL1, LH1, HL1 and HH1) by applying DWT (Mallat, 1989). The sub-band LL corresponds to estimating wavelet coefficients and sub-bands labeled as LH, HL and HH correspond to full wavelet coefficients. To find the wavelet coefficient of another decomposition level, LL alone is considered. This provides a second level wavelet corresponding and decomposition sub-bands are LL2, LH2, HL2 and HH2. Till the third level, the process is continued. The energies (using L1 norm) and wavelet coefficients, standard deviations are calculated for 10 sub-bands i.e. LHi, HLi, HHi; for i = 1, 2, 3 and LLi; for i = 3 [6].

IV. Color feature extraction

Color is one of the most significant feature of image retrieval. It performs a vital role in the human visual perception mechanism. It is a specification of coordinate system or subspace within the system where each color, is

DOI- 10.18486/ijcsnt.2016.5.1.02
ISSN-20536283

represented by a single point. Numerous color spaces are available RGB, CMY, CMYK, HSV, etc. [4]. Color features can be categorized into histogram and statistical models.

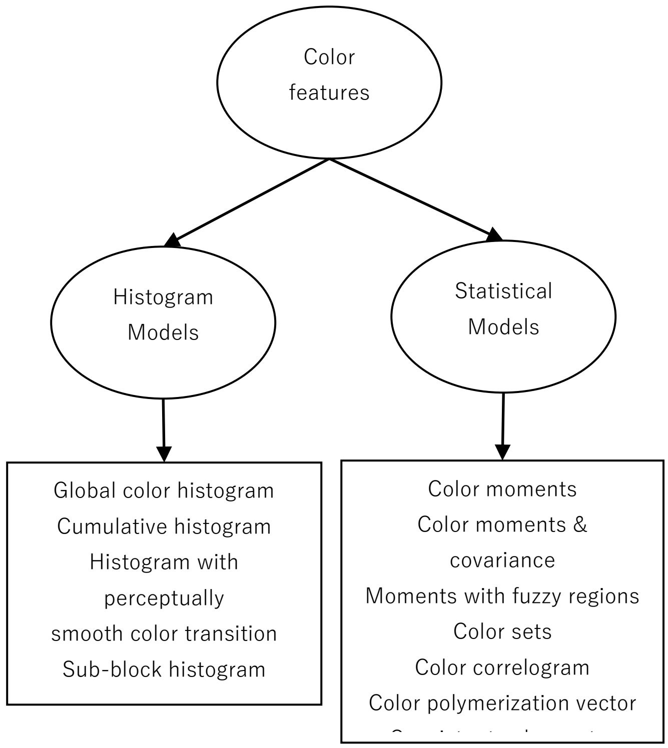

Figure 2: Classification Of Color Feature

Swain and Ballard proposed the concept of retrieval method using color characteristics. There are many color histograms available such as global color histogram, cumulative histogram and sub-block histogram. Statistical model of color representation was proposed by Stricker M and Orengo M. Color correlogram presents the probability of finding color pairs at a fixed distance of pixel and it provides spatial information. Therefore color correlogram gives better retrieval accuracy in comparison to color histogram. Color correlogram is superset of color autocorrelogram, color autocorrelogram captures the spatial correlation between same colors only. Rui Min, H.D. Cheng proposed Dominant Color Descriptor which defines salient color distributions in an image or interest and provides region and an effective, compact and also intuitive representation of colors presented in an image.

V. Shape Feature Extraction

Shape is a significant visual feature which is used to describe the image content. Shape can be described as a part of that space occupied by the thing, as decided by way of its outside boundary, abstracting from an area and orientation in housing, measurement and different homes.

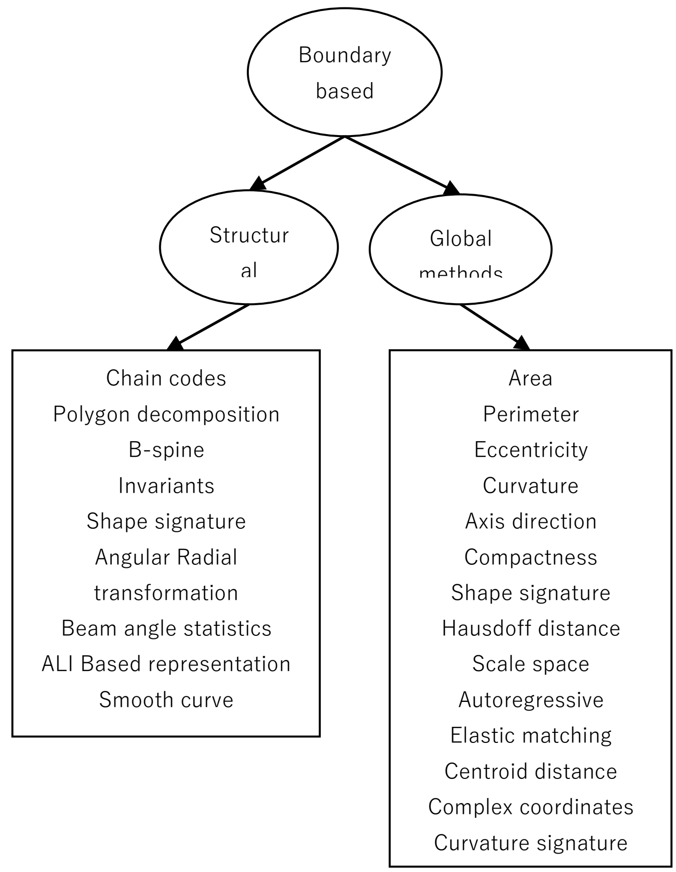

Figure 3: Classification of Boundary Based Shape Descriptors

Efficient shape aspects must acquire the following properties: identifiability, translation, noise resistance, affine invariance, reliability and statistically independent. MPEG -7 has set several terms to measure a shape descriptor based on compact features, good retrieval accuracy, computational complexity, retrieval performance and retrieval accuracy as proposed by H. Kim & J. Kim. [4]. However, an alluring shape descriptor ought to be application free. An important characteristic of a desirable shape descriptor is its low computational complexity. In general, representation of shape and description methods may also be categorized into two different classes: i.e. boundary approaches and area headquartered methods. These methods are also categorized into structural methods and global methods.

This classification is based on whether the shape is represented by portions or segments. They can be further divided into transform domain and spatial domain. Contour

shape techniques represent shape boundary information which describes two types of approaches:
1. **Continuous approach (global)**: They do not divide the shape into sub-parts, shapes are described by a feature vector.
2. **Discrete approach (structural)**: They break the shape boundary into segments, final representation is a string or a graph.
I. Young, J. Walker, J. Bowie used various worldwide descriptors, for example zone, circularity, unconventionality, significant pivot introduction and twisting vitality. They are utilized as channels to take out false hits or mixed with other form descriptors to segregate shapes. They are not suitable for standalone shape descriptors. M. Peoria, J. Livarinen described various descriptors, including convexity, proportion of rule pivot, round about change and elliptic fluctuation. B. Scassellati, S. Alexopoulos, M. Flickner used a classical distance measure Hausdorff distance.
Shape can be represented as a one dimensional function using Shape signature, derived from shape boundary points as proposed by D. S. Zhang, G. Lu such as centroid profile, complex coordinates, cumulative angle, centroid distance, tangent angle, curvature, area and chord-length.
Structural Methods: In this approach shapes are broken down into boundary segments called primitives. Common methods for boundary are polygonal approximation, curvature decomposition and curve fitting used by T. Pavlidis. H. Freeman introduced chain codes to describe an object using a sequence of of unit size line segment with the given orientation.
Region Based Methods: All the pixels, within a shape region are taken into account to obtain the shape representation in region based methods. Moment descriptors are used by common region based methods to describe shapes. Grid method, shape matrix, convex hull and media axis methods also fall into common region based category. Various region based methods are represented as shown in the figure 4. A shock graph is a descriptor based on the medial axis. The medial axis have been proposed as a useful shape abstraction tool for the representation and modeling of animated shapes. Skeleton and medial axes have been extensively used for characterizing objects satisfactorily using structures that are composed of lines or arc patterns. The medial axis is an image processing operation which reduces input shapes to axial stick-like representations. For both Contour and regions of a shape, one can use moment's theory to analyze the object various moments.

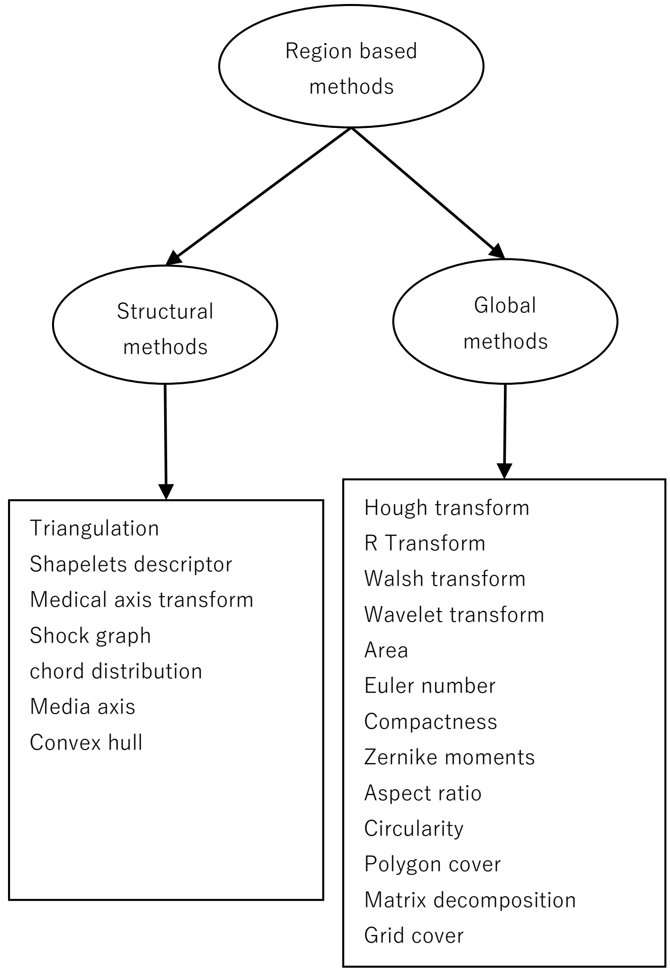

Figure 4: Classification Of Region Based Shape Descriptors

VI. Texture Feature Extraction

According to Sklansky, if a set of local statistics or other local properties in image are steady, then the image is said to have constant texture. According to Vassilieva, texture gives the structural information of surfaces and objects in the image. It depends on the distribution of intensity over the image. Contrast and sharpness are the parameters which can describe texture analysis and attains scalability and periodicity properties. Texture analysis methods can be classified into various categories, in this paper, we have classified them into two categories-spatial domain and wavelet domain as represented in figure 5. Angular Radial Partitioning Intensity Histogram was a two dimensional histogram proposed by Quin et al. An approximation to Earth Mover’s Distance (EMD) was proposed by Kristen Grauman and Trevor Darrell. The co-occurrence matrix method can be categorized into gray level and ordinal measures. The concept of Gray level Aura Matrices (GLAM) to model, texture images was proposed by Xuejie

Qin & Yee-Hong Yang. In order to obtain better accuracy, signed distances of the image of the boundary obtained using an SVM learning algorithm was proposed by Guodong Guo, Hong-Jiang Zhang & Stan Z Li.

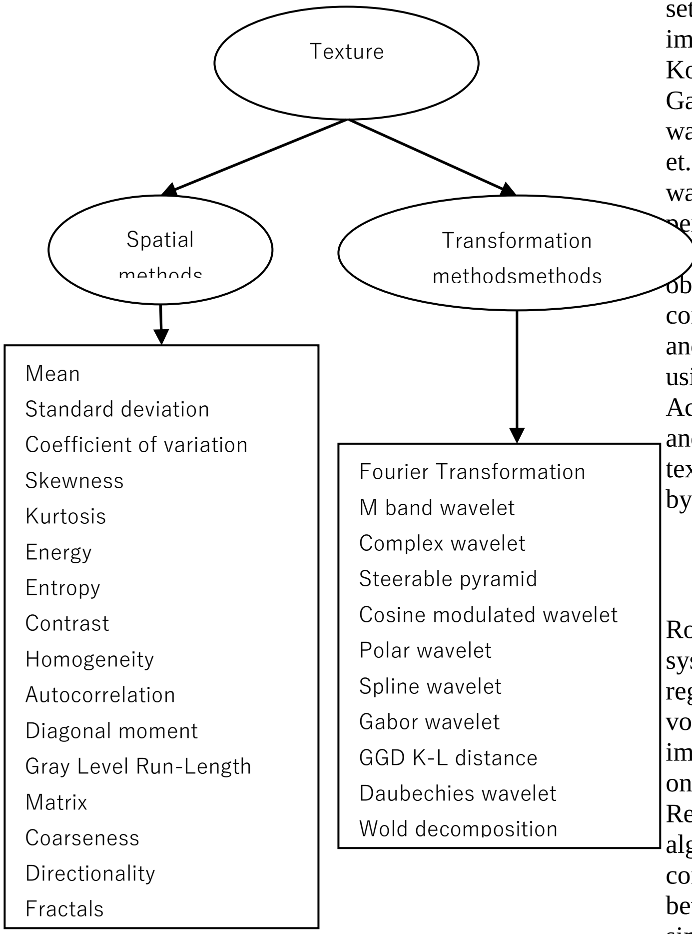

Figure 5: Classification of Texture Descriptors

Ordinal Co-occurrence Matrix, which used a combination of co-occurrence matrix and ordinal measures, was used by Mari Partio, Bogdan Cramariuc & Moncef Gabbouj. A great improvement in the retrieval process was achieved by determining Gower’s similarity coefficient obtained by using the autoregressive model and perceptual model by Noureddine Ennahnahi. Marco Carcassoni, Eraldo Ribeiro & Edwin R Hancock determined the modal analysis methods . Timothy F. Cootes, Gareth J Edwards & Christopher J Taylor described active appearance model which improved texture match with the minimization of texture error. George L Gimel’farb & Anil K Jain used Markov Random Field image model which can tolerate texture rotation and scale to a certain extent. Co-occurrence matrices, fractal geometry, random field modeling and Gabor filtering were used by P.P.Ohanian & R C Dubes. A statistical analysis of SASI for texture image retrieval was proposed by A Carkacioglu & F Y Vural. Daubechies wavelet for determining the wavelet coefficients as image features were used by James Ze Wang, Gio Wiederhold, Oscar Firschien and Sha Xin Wei. A Steerable Pyramid based method where weighted norm between two feature sets and symmetrized version of the KL divergence for image matching was used by Blancho Patrice & Hubert Konik. Improving the retrieval performance by using the Gabor features for learning the similarity as feature space was used by W Y Ma & B S Manjunath. Yu-Long Qiao et.al. found that Cubic bi-directional orthogonal spline wavelest and quadratic spline dyadic wavelet give better performance. Polar Wavelet for image retrieval was used by Chi Man Pun. Manesh Kokare, P K Biswas & B N Chatterji obtained improved retrieval performance by using rotated complex wavelet filter (RCWF), DT_CWT. An adaptive and unsupervised segmentation method for texture images using M-Band wavelet transform was verified by M. Acharya & M K Kundu. Cosine modulated wavelet based and cosine modulated wavelet packet based concepts for texture features obtained better accuracy and retrieval time by Manesh Kokare, P K Biswas & B N Chatterji.

VII. Literature survey

Romain Raveaux (2013) [7] et. al present an automatic system to retrieve and annotate images. Here assume that regions in an image can be defined by using a blob vocabulary. Blobs are produced from the features of an image by applying clustering. Features are nearby removed on regions to capture Color, Shape and Texture knowledge. Regions are processed through an effective segmentation algorithm. Images are structured into various locale contiguousness charts to consider spatial connections between districts. This representation is utilized to achieve a similitude look into a picture set. Thus, the client can express his requirement by giving an input image, and from that point getting as similar images as an output. Here graph based method is benchmarked to conventional Bag of Words approaches. Outcomes have a tendency to uncover a decent conduct in order of our diagram construct arrangement with respect to two different publicly presented databases. Experiments illustrate that a structural method needs a smaller vocabulary size to reach its best performance.

H. B. Kekre (2013) [8] et al explores a new and simple method for extraction of features for CBIR systems. It tries to enhance the retrieval accuracy of a CBIR system along with decrease in feature vector dimension. The feature extraction procedure is based on bins method. Information of image is stored into eight bins formed through partitioning histogram applying CG. The image is separated into R, G and B planes. For all planes normal and equalized histograms are calculated. Histograms are partitioned in two one-of-a-kind parts and image contents are segregated into eight boxes. The image features are extracted to 8 packing containers, are represented to have made use of first four statistical moments. Characteristic vector databases are ready for each four moments. Each feature vector database is tested by applying the same query images set fire on them. Query and database of image feature vectors are then compared by using three comparability measures to be specific Euclidean separation ED, Absolute separation AD and Cosine relationship separation CD. Results are evaluated by using three parameters PRCP i.e Precision Recall Cross over the Point, LS: Longest String and string of LSRR Length to retrieve each central image from database. The process proposed in this paper is experimented with a database of 2000 BMP photographs containing 20 special lessons from numerous sources containing Wang database. All classes include 100 images of its own category.

H. B. Kekre (2014) [9] et al presents that CBIR is one of the most famous field of computer vision containing big scope for researchers to work out on the new concepts that will give the promising outcomes. This paper explores all of its phases. Feature extraction phase is based on 8 bins method that surely works for dimension reduction. Bins are the characteristic vector add-ons obtaining the picture contents. This method is dealing mostly with texture and color image contents. Composition substances are removed as measurable minutes while color contents and their role in the procedure is evaluated through applying Four color areas specifically, RGB, XYZ, LXY, and L’X’Y’ color areas. Three closeness measures Euclidean separation, Cosine connection separation and Absolute separation are utilized to see the assessment of query and database image elements. Performance of bins method in each of four color spaces is evaluated through three parameters PRCP, LS, and LSRR.

Bae-Muu Chang (2013) [10] et al presents an approach in which CBIR system is using three kinds of visual features and 12 distance measurements, which is optimized through the PSO algorithm. For convenience, it is called CBIRVP technique hereafter. First, CBIRVP technique extracts three kinds of features: color, texture, and shape. Subsequently, an item employs appropriate distance measurement for all types of features to calculate similarities between a query image and images available in the database D. Additionally, the PSO algorithm is utilized to optimize the CBIRVP technique through searching for almost most reliable combinations between facets and their corresponding similarity measurements, as well as finding out the approximately finest weights for 3 similarities with respect to three kinds of features which are being used. Finally, experimental outcomes demonstrate that CBIRVP technique outperforms in comparison to other existing approaches considered here.

Nishant Shrivastava (2013) [11] et al presents a new method for image retrieval based on the selective regions matching by using region codes. Each image in the database is uniformly divided into different multiple regions and all regions are assigned a 4-bit vicinity code centered upon its location relative to the valuable region. Dominant colors and LBP established texture aspects are extracted from these regions. Feature vectors in combination with their neighborhood codes are stored and listed in the database. At the time of retrieval, feature regions vectors containing area codes like query image locale are utilized for correlation. To mirror the user's input query formulation in an improved way, an effective method for ROI covering square determination is likewise proposed. District codes are further used to discover relative multiple ROIs locations in query and target image. The execution of the proposed technique is performed on the MPEG-7 CCD database and the Corel image database.

Ahmed Talib (2013) [12] et al present that Color has been widely used in the image retrieval process. The DCD that was proposed through MPEG-7 is a famous case in this point. It is based on efficiently describing an image or a region prominent color. In this paper, a novel approach for extraction of the semantic feature from dominant colors (weight for all DC) is proposed. The newly proposed method helps to decrease the image background effect on the decision matching of image where an object’s colors receives much extra focus. Likewise, a change in DC-based comparability measure is additionally proposed. Experimental outcomes reveal that the proposed descriptor with similarity measure achieves improvement over the current descriptor in CBIR application. The proposed descriptor considered as venture forward to the article based image recovery.

Deying Feng (2013) [13] et al present an efficient indexing technique for CBIR. The proposed technique presents ordered quantization to growth the respect among the quantized characteristic descriptors. Accordingly, the characteristic factor correspondences can be decided through quantized function descriptors, furthermore, they are utilized to quantify comparability between the input image and image database. To implement above method efficiently, a multi-dimensional inverted index is proposed to compute various feature point correspondences, after which approximate RANSAC is investigated to approximate the spatial correspondences of functional features between the input image and candidate image back from the multi-dimensional inverted index. The experimental outcomes demonstrate that this indexing technique increases the retrieval efficiency while confirming the retrieval accuracy in the CBIR.

Savita Gandhani [14] et al presented a new method for CBIR through combining the low level feature i.e. color, texture and shape features. At first, conversion in the shading space from RGB model to HSV mode takes place, and after that separation of shading histogram is done to form color feature vector. Next, extracting the texture feature by applying BDIP and BVLC moment. At last, here by using a Canny edge detector to extract the shape features. Finally, we combined the color, texture and shape features to form feature vectors of the complete image. Experimental outcomes present that the proposed procedure has a very good performance with respect to the precision and recall when compared with other different approaches.

Fazal Malik (2012) [15] et al present that efficient CBIR systems require an effective low level feature extraction for better performance, for example color, texture and shapes can be used for indexing and fast computation of similarity match between the input image and indexed images for content based image retrieval systems. Points are removed from the pictures in pixel and compacted areas. Now the vast majority of the current portraits is in compressed format for example JPEG applying DCT. This paper presents the issues of efficient feature extraction and the effective images matching in the compressed domain. In this technique histogram statistical texture features are first quantized then they are extracted from the image DCT blocks by using the DC important energy and the first three AC coefficients of the blocks. For the effective input image matching with images, numerous distance metrics are used to measure similarities by using texture features. The analysis of the performance measurement of CBIR system is based on the basis of numerous distance metrics in various numbers of quantization bins. The proposed technique is tested on a Corel image database and the experimental outcomes present that technique has robust image retrieval for numerous distance metrics with various histogram quantization in a compressed domain.

Gholam Ali Montazer (2015) [16] et al presents two novel approaches as descriptors of an image. The basis of the proposed approaches is built upon SIFT algorithm. When it comes to choosing an effective and realistic features for extraction SIFT is an appropriate choice. After extraction of image feature SIFT, k-means clustering is applied on feature matrix extracted through SIFT, and then two novel types of dimensionality reductions are applied in order to obtain SIFT features. Applying the proposed schemes cannot only exploit the SIFT features advantage, but also can reduce extreme requirement of the memory storage to store SIFT features.

Menglin Liu (2015) [17] et al present Texture is a significant feature usually used in the CBIR. Classical approaches of computing texture feature ignore texture features obtained through chroma differences. A novel technique of calculating chroma texture features is proposed in this paper. Huge numbers of experiments are improved and proved that the chroma texture feature is most significant complement to the classical luminance texture. The image retrieval performance is improved significantly by using a combination of luminance composition and chroma surface with a lower-dimensional vector. The normal positioning proportion is improved by 14.57 %, and there is an obvious improvement in the average recall-precision curve.

Cyril Höschl IV (2016) [18] et al present histogram-based image retrieval technique which is designed exactly for noisy query images. Based on histogram similarity images are retrieved. To achieve robustness to noise, the histograms are defined through newly proposed features which are insensitive to a Gaussian additive noise in the original images. The advantage of this technique is proved theoretically and demonstrated experimentally on real data.

VIII. Conclusion

CBIR is an active research area in the recent era. Content-based image retrieval is an application of computer vision, that is searching similar images in a huge database of images. In this paper, we present a study on various available CBIR systems and literature survey as well. By using different methodologies for Feature extraction, better and more accurate retrieval rate can be ensured. In order to enhance effectiveness of any CBIR system, discovery of semantically meaningful pattern is desired.

References

[1]. Ekta Gupta and Rajendra Singh Kushwah," Combination of Global and Local Features using DWT with SVM for CBIR", in 4th *IEEE Int. Conf. ICRITO*, pp. 1-6, 2015.

[2]. Houssem Chatbri, Paul Kwan, and Keisuke Kameyama," A Modular Approach for Query Spotting in Document Images and Its Optimization Using Genetic Algorithms", *IEEE Congress on Evolutionary Computation (CEC),* pp. 2085-2092, 2014.

[3]. Snehal Mahajan and Dharmaraj PatiI," Image Retrieval Using Contribution-based Clustering Algorithm with Different Feature Extraction Techniques", *IEEE Conf. IT in Business, Industry and Government (CSIBIG)*, pp. 1-7, 2014.

[4]. Chesti Altaff Hussain, Dr. D.Venkata Rao and Dr. S.Aruna Mastani," Low Level Feature Extraction Methods For Content Based Image Retrieval", *IEEE Int. Conf. on Electrical, Electronics, signals, communication and optimization (EESCO)*, . 1-5, 2015.

[5]. Shiv Ram Dubey, Satish Kumar Singh and Rajat Kumar Singh," Local neighborhood-based robust color occurrence descriptor for color image retrieval", *IET Image Processing*, pp. 578–586, 2014.

[6]. Sudipta Mukhopadhyay, Jatindra Kumar Dash and Rahul Das Gupta," Content-based texture image retrieval using fuzzy class membership", *ScienceDirect Pattern Recognition Letters 34*, pp. 646–654, 2013.

[7]. Romain Raveaux, Jean-Christophe Burie and Jean-Marc Ogier," Structured representations in a content based image retrieval context", *ScienceDirect J. Vis. Commun. Image R. 24*, pp. 1252–1268, 2013.

[8]. H. B. Kekre and Kavita Sonawane," Use of Equalized Histogram CG on Statistical Parameters in Bins Approach for CBIR", *ICATE* Paper Identification No. 64, pp. 1-6, 2013.

[9]. H. B. Kekre and Kavita Sonawane," Comparative Study of Color Histogram Based Bins Approach in RGB, XYZ, Kekre's LXY and L'X'Y' Color Spaces", *IEEE Int. Conf on Circuits, Systems, Communication and Information Technology Applications* (CSCITA), pp. 364- 369, 2014.

[10]. Bae-Muu Chang, Hung-HsuTsai and Wen-LingChou," Using visual features to design a content-based image retrieval method optimized by particle swarm optimization algorithm", Elsevier, pp. 1-11, 2013.

[11]. Nishant Shrivastava and Vipin Tyagi," Content based image retrieval based on relative locations of multiple regions of interest using selective regions matching", *Information Sciences ScienceDirect*, pp. 1-13, 2013.

[12]. Ahmed Talib, Massudi Mahmuddin, Husniza Husni and Loay E. George," A weighted dominant color descriptor for content-based image retrieval", *ScienceDirect J. Vis. Commun. Image R*. vol. 24 pp. 345–360, 2013.

[13]. Deying Feng, JieYang and Congxin Liu," An efficient indexing method for content-based image retrieval", *ScienceDirect Neurocomputing* vol. 106, pp. 103–114, 2013.

[14]. Savita Gandhani, Rakesh Bhujade and Amit Sinhal," An Improved And Efficient Implementation Of CBIR System Based On Combined Features", *IEEE Int. Conf. CIIT*, pp. 353-359, 2013.

[15]. Fazal Malik and Baharum Baharudin," Analysis of distance metrics in content-based image retrieval using statistical quantized histogram texture features in the DCT domain", *Journal of King Saud University – Computer and Information Sciences*, vol. 25, no. 2, pp. 207–218, 2013.

[16]. Gholam Ali Montazer and Davar Giveki," Content based image retrieval system using clustered scale invariant feature transforms", *ScienceDirect Optik* 126, pp. 1695–1699, 2015.

[17]. Menglin Liu, Li Yang and Yanmei Liang," A chroma texture-based method in color image retrieval", *ScienceDirect Optik* vol. 126, pp. 2629–2633, 2015.

[18]. Cyril Höschl IV and Jan Flusser," Robust histogram-based image retrieval", *ScienceDirect Pattern Recognition Letters 69*, pp. 72–81, 2016.