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COMPREHENSIVE ANALYSIS OF SOME RECENT COMPETITIVE CBIR TECHNIQUES

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Abstract

In today's real life applications complexity of multimedia contents is significantly increased. This is highly demanding the development of effective retrieval systems to satisfy human desires. Recently, extensive research efforts have been carried out in the field of content-based image retrieval (CBIR). These research efforts are based on various parameters; feature extraction (to find content of image), similarity matching (compare the content of a query image with content of other images), indexing (index images based on their content), and relevance feedback (consider users view to get better output). The efforts result many promising solutions in designing effective and interactive CBIR systems. This paper mainly includes study of some recent CBIR techniques with the goal to design efficient system. Additionally, this study presents a detailed framework of CBIR system. Further it includes improvements achieved in the major areas like feature extraction, indexing, similarity matching, relevance feedback.

Keywords:

Content Based Image Retrieval (CBIR), Feature extraction, Indexing, Relevance feedback

1. INTRODUCTION

Due to exponential growth of imaging devices such as digital camera and scanner, multimedia contents are massively generated and used [1][2][3]. If there is no computer aided browsing, searching and retrieving mechanism to obtain the desire content, all this data is nearly useless.To use this enormous data for particular purpose, need an effective method which allows retrieving data according to interest of user. The content based image retrieval provides a hopeful solution to this problem. Content based image retrieval (CBIR), is a technique, which uses the visual content to search the images from large scale image database as per user's interest [1][2][3][4][5]. It matches the features of the query image with that of image database through some image-image similarity evaluation. In the CBIR system, the input is in the form of image and the output produce is not a single image, but it is the list of images.

To develop an efficient CBIR system a lot of work has been done in this field. In recent years, CBIR has drawn much interest of many researcher contributing new solutions and techniques.Most of research in this area is based on low level feature extraction like color, shape and texture [2][3][4][6] Although low-level feature extraction methodologies produces good result, such systems cannot be effectively used by a learner due to semantic gap between users perception and understanding. So bridging the gap between low-level and high-level (semantic) feature is emerged as a promising area of research [2][3][4]. To get quick output matching contents of query image and that of images in databases, is needed so there is a necessity of matching techniques [1][2][3][4]. Relevance feedback [1][2][3]treats the retrieval session as repetitive query reformulation operations. It presents retrieved images to the user after submitting query image(s) and solicits user's relevance judgments over the course of several rounds of interaction. It also proves prominent area of research in order to develop interactive CBIR systems. To efficiently access desire images, ranking [2][3][4] of output images based on some factors, emerges another area of research in the field of CBIR system.

2. GENERAL FRAMEWORK FOR CONTENT BASED IMAGE RETRIEVAL SYSTEM (CBIR)

This section describes the complete framework of content based image retrieval system. It consists of different and correlated components. The following figure shows a general framework of CBIR [1][4].

The retrieval process begins with the submission of query image to the system. Both the query image and all images in the database are processed and represented in the same way in order to retrieve only relevant images. Then some preprocessing methods (if required) might be applied to the image which mainly depends on the aim of the retrieval application. For instance, the image could be segmented into many smaller blocks or regions that are further processed to represent some image objects. In addition, these smaller parts of the image might be classified or clustered in some categories to be used as region-based retrieval or for learning purposes. Other preprocessing tasks include image resize, rescale, de-noise, etc.

Feature extraction is next main step in the process. Visual/textual descriptors are extracted from images and represented in certain way into the data space. Some common extracted features are color, texture, shape or local descriptors. Some techniques apply some preprocessing tasks such as classification or spatial processing after feature extraction, thus the preprocessing of images could be conducted before or after feature extraction.

Finally, the system computes the distance between the transformed features of query image and all images in the database in order to return the most relevant images based on some distance measures.

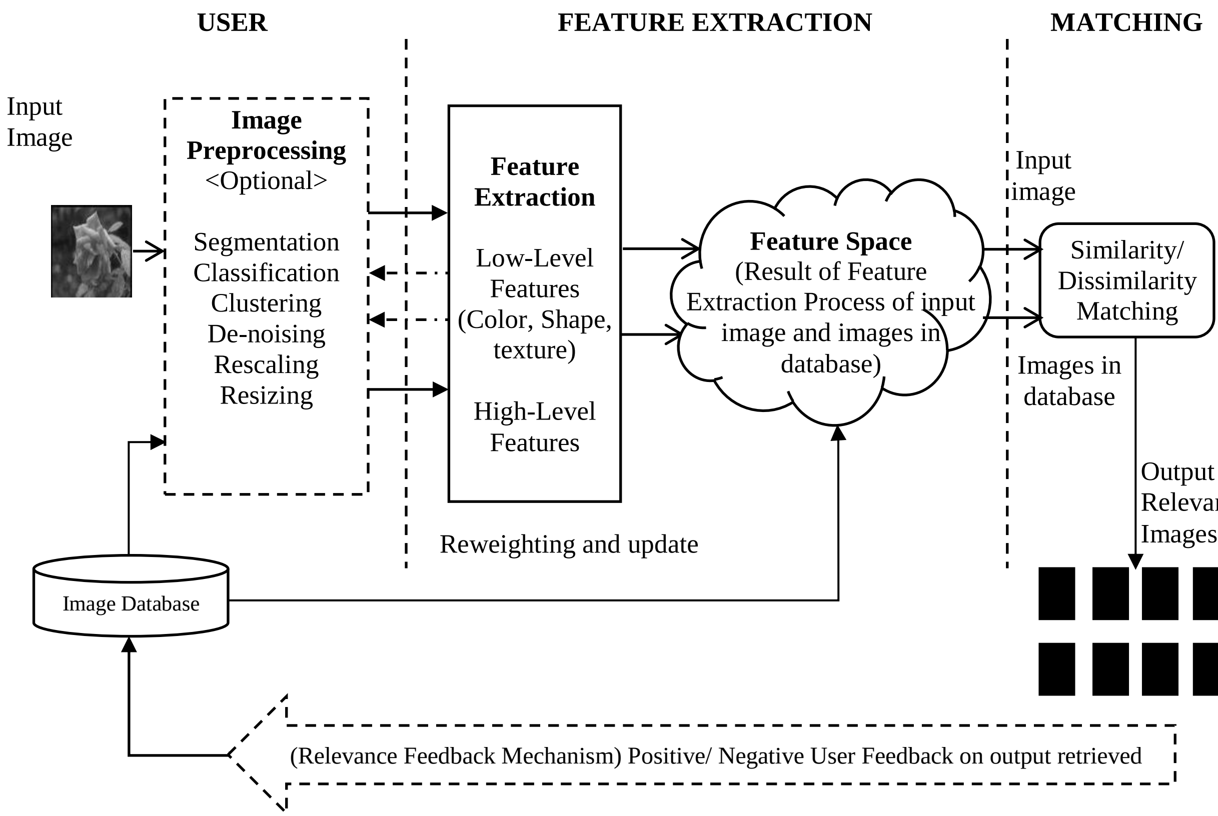

Fig.1. General Framework of CBIR System

The returned images are usually presented as a ranked list. Some retrieval approaches enable users to decide the relevancy degree of retrieved images as a satisfaction measure, i.e. relevance feedback. The returned images are usually presented as a ranked list. Some retrieval approaches enable users to decide the relevancy degree of retrieved images as a satisfaction measure, i.e. relevance feedback. This may improve the accuracy of retrieval by updating the query and similarity measures according to the user's preferences. Automatic feedback and system self-training are preferred for reducing the user intervention and avoiding multiple iterations of refinements.

Data visualization being an integral part of the CBIR framework, recently perceived a significant utilization. This addresses the problem of designing graphical user interfaces (GUI) for image representations, query submission and refinement, relevance feedback and browsing mechanisms. A proper visualization during human-machine interaction guarantees the improvement of retrieval accuracy, maximum flexibility with minimum complexity, and intuitive retrieval environment.

3. RECENT CBIR SYSTEMS

To overcome the challenges faced by CBIR system, various techniques are developed by different researchers in recent years. They focused to overcome the limitations found in previous work by suggesting some new methods and techniques. This will help to generate more efficient and interactive CBIR systems. The next section includes some of the recent techniques/methods used to develop CBIR system. Research work done in CBIR system is divided among four major areas namely feature extraction, similarity matching, indexing and relevance feedback. The working in these areas is not completely independent, but depends on each other.

3.1 FEATURE EXTRACTION

Feature extraction plays crucial role in designing of any CBIR system. A good visual content descriptor should be unaffected to the accidental alteration introduced by the imaging process [1]. There are two types of visual contents (features) in CBIR: primitive (low-level) features and domain specific (high-level) features. The primitive feature includes color, shape, and texture while domain specific features includes for instance, fingerprints, handwriting, and human faces, is application dependent and may involve domain knowledge. Feature extraction is the method to find visual contents (feature) of image like color, shape, texture or any combination of it [1][2][3]. The use of specific feature depends on the specific image processing application. However, the most of the system uses combinations of these features for more accurate results. However, MPEG-7 standard feature extraction algorithm is also used in some cases [3].

3.1.1 CBIR System with Low Level Feature:

Color is the most widely used visual content for image retrieval. Its three-dimensional values make it superior to describe image contents than the single dimensional gray values. Color space must be identified before selecting an appropriate color descriptor. Many color description has been found like color moments, color histogram, color coherence vector, color correlogram etc. [1][2][3][4].

Another important property to represent image is texture. There are two types of texture descriptors; structural and statistical. Structural methods, includes morphological operator and adjacency graph which describes texture by identifying structural primitives and their placement rules. These features found to be most effective when applied to regular structures. Statistical methods, includes 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 wavelet and Gabor transform. Statistical distribution uses image intensity to characterize an image [1][2][3].

Shape features of objects or regions are also required in many applications. Shape features unlike color and texture are usually described after images segmentation into regions or objects. As it is hard to perform accurate and perfect image segmentation, the shape features for image retrieval are application oriented. The shape description methods can be categorized into boundary-based and region-based methods. A good shape descriptor for an object should be able to handle translation, rotation and scaling [1][2][3].

In literature many CBIR system using low-level features are found. Some example includes Chabot[7] developed by Department of Computer Science, university of California, USA, represents each image using the Color histogram. Other systems such as C Bird [7] developed by school of computing science, Canada , CHROMA[7], developed by School of computing engineering and technology, Sutherland, U.K. uses color vector to represent each images. ADL [7], developed by University of California, Santa Barbara, CBVQ[7], developed by Image and advance television lab, Colombia, CIRCUS[7] user texture features to represent the image. SQUID[7], Center for Vision speech and signal processing, University of Surrey, UK, SYNAPSE[7], developed by Centre for intelligent, Information retrieval, uses the pure shape features to developed the system.

In this section some recently developed CBIR system using low level features are discussed.

Jaehyun A et al. (2014) [6], propose an object-based color image retrieval algorithm using the spatial distributions of colors in the salient regions. The proposed method first extracts the salient object regions using a color contrast approach, and finds a few dominant colors for each salient region. Then, the spatial distribution of each dominant color is modeled as a binary map. The binary map defines the spatial distribution of dominant color in the salient region, which considers the object shapes with the same color. A matching method has also been proposed to evaluate the similarity of binary maps. According to the experiments using several color image databases, the proposed method is shown to provide better retrieval performance than the conventional and previous color-based methods.

Izem H et al. (2015) [8], propose a new feature extraction method based on texture segmentation. The method first fixes a converging point α. It determines Main analysis Window (MW) starting from α to the bottom left corner of the image. Then several probable windows are extracted and further from each window the feature extracted using appropriate method. Finally, using similarity measure the window is decided whether relevant or not. This process is repeated until the size of the MW reaches a minimum size. Each significant window increases the relevance of the desired texture in the output image. At the end, an image of relevance is obtained by considering the most relevant area.

Shaoyan Sun et al. (2015) [9], deal with the fundamental issue of image representation to improve the retrieval performance. Here a novel image retrieval framework is proposed with compact image representation from generic object regions. It first identifies regions of interest with a generic object detector. The fusion of the CNN and VLAD features is used to describe the detected regions, for a more effective representation. This representation is efficient in memory overhead, and the retrieval process is time efficient.

Kommineni J et al. (2015) [10], present a new content based image retrieval approach based on the database classification using Support Vector Machine (SVM) and color string coding feature selection. The paper handles fundamental issue to select the image features that the best represent the image contents in a database in designing any CBIR system. The feature extraction is done using color string coding and string comparison.

Menglin L et al. (2015) [11], propose a new method of calculating chroma texture. Large numbers of experiments are performed which proves that the chroma texture feature was a very important supplement to the traditional luminance texture. However, combination of luminance texture and chroma texture with a lower-dimensional vector, significantly improves the effectiveness of the image retrieval.

3.1.2 CBIR System with High Level Feature:

As low-level features are not sufficient to represent the image contents properly, leads to number of mismatches in the output. Therefore high-level features (semantic features) are used to develop the system. These high-level contents are obtained by textual description or by complex inference procedures based on visual content [1][2][3][4]. Some recent CBIR systems which use semantic (high level) features are discussed in next section.

Michal B et al. (2013) [12], address the problem from a general perspective and presented a new annotation model that allows to combine different image and text-processing techniques. In the experimental evaluation, it focused on the web image annotation task and demonstrated that the annotation quality can be significantly improved by combining various expansion techniques.

Zhiyong C et al. (2014) [13], document a set of comprehensive experiential studies on large social images showing the effects of multiple query evidence. The search performance based on the social tags, different kinds of visual features and their combinations are systematically studied and analyzed. A novel quantitative metric is proposed to calculate the visual query complexity. It is applied to evaluate the influences of different visual queries based on their complexity levels.

Hanwang Z et al. (2014)[14], propose a novel attribute-augmented semantic hierarchy (A2SH) which organizes semantic concepts from general to specific and augments each semantic concept with a set of related attributes. This is specifications of the multiple facets of the concept and act as an intermediate bridge connecting the concept and low-level visual features. Here the concepts of classifiers, attribute classifiers, and hierarchical similarity function were discussed. Based on the proposed A2SH, the developed a unified content-based image retrieval system supports both automatic retrieval and interactive retrieval with user feedback. A hybrid feedback mechanism was developed to collect a broad array of feedback based on both attributes and images. This feedback then use to improve the retrieval performance based on A2SH.

Alex Papushoy et al. (2015) [15] propose the query by saliency content retrieval (QSCR), image retrieval method. It is based on human visual attention models. In the system, each image is segmented and a set of characteristic features is calculated for each region. Based on the perceived saliency, the weight is assigned to each region. Image similarity is evaluated using Earth Mover's Distance (EMD). This automated method outperforms another approach using visual attention.

3.1.3 CBIR System with Combination of Features:

The use of particular feature depends on the specific image processing application. However, most of the system uses combinations of these features for more accurate results. In literature Photo Finder [7], developed by the Alta Vista, uses the color, shape and texture features, Blob world [7], CANDID [7], Draw Search [7] also uses all three features collectively to develop system. Recently developed CBIR systems that use combination of features are discussed in next section.

Romain R et al. (2013) [16], propose an automatic system to annotate and retrieve images. It assumes that regions in an image can be described using a vocabulary of blobs. Blobs are generated from image features using clustering. Features are locally extracted on regions to capture Color, Texture and Shape information. Regions are processed by an efficient segmentation algorithm. Images are structured into a region adjacency graph. With adjacency graph, it is easier to map spatial relationships between regions. This representation is used to perform a similarity search into an image set. Hence, the user can express own need by giving a query image, and thereafter receiving as a result all similar images.

Emir S et al. (2014) [17], present a new idea to extract Fourier descriptors from the simplest shape signature – complex coordinates. Here, the sum of magnitudes of all harmonics is used, rather than using scale normalization with the magnitude of the first harmonic. This leads to improve shape scale normalization. All the experimental results indicate that the method proposed outperforms many other state of-the-art Fourier descriptors based methods, as compare to retrieval performance and computational time.

Cong B et al. (2015) [18] propose K-means based histogram (KBH) method using combination of color and texture for better performance. Here, multi-resolution feature vector (combination of color and texture) is generated from coefficients of Discrete Wavelet Transform (DWT). K-means algorithm is used to partition the vector space which will reduce number of histogram bins. With fusion of z-score normalized Chi-square distance similarity measures the proposed method gives the improved retrieval performance.

Anu Bala et al. (2015) [19], propose local text on XOR patterns (LTxXORP), a new descriptor for content-based image retrieval. This method gathers the text on XOR pattern which results in the structure of the query image or image in database. The feature vector is constructed based on the LTxXORPs and HSV histograms. The performance of the proposed method is evaluated by testing on benchmark database, Corel-1K, Corel-5K and Corel-10K in terms of precision, recall, average retrieval precision (ARP) and average retrieval rate (ARR). The method proposed show a significant improvement for image retrieval.

Jing-Ming G et al. (2015) [20], present a new approach to index color images using the features extracted from the error diffusion block truncation coding (EDBTC). The EDBTC produces two color quantizers and a bitmap image. These quantizers and bitmap image is then processed using vector quantization (VQ) results in image feature descriptor. Here, two new features are used color histogram feature (CHF) and bit pattern histogram feature (BHF), to compare the similarity between a query image and the target image in database. The difference obtained from CHF and BHF is used to measure the similarity between two images.

Min H et al. (2015) [21], present multi-feature fusion method which combines the color moment in RGB color space and color histogram in HSV color space for color feature extraction. The shape based features are extracted using improved Zernike moments and the texture feature extraction is done using gray level co-occurrence matrix. It combines these three features to describe an image. Finally, the experimental results are shown using color features, shape features, texture features as well as the fused features. The results show that the image retrieval method based on multi-feature combination has better retrieval performance.

3.1.4 Feature Extraction based on Standard Descriptors:

Some standard descriptors like MPEG-7 and SIFT are also used to develop the CBIR system. The main advantage of these descriptors is its interoperability.

Suraya A et al.(2013) [22], presents an approach using Scale Invariant Feature Transform (SIFT) algorithm for binary and gray scale images. As SIFT is invariant to scale, rotation and translation and it partially invariant to alteration and illumination changes. Due to these fundamental properties of SIFT, it is used for development of robust CBIR by usingMPEG-7, COIL-20 and ZuBuD image databases. The approach first detects keypoints from images and further it is used to match between the query images and images from the database.

Yusuke M et al. (2014) [23], propose magna image retrieval using a sketch-based method. Here users can draw sketches via a Web browser; these sketches considered as an input to the system. It further results in list of similar images from a magna database. The nature and characteristics of manga images are different as compare to natural images. To retrieve manga images effectively a fine multi-scale edge orientation histogram (FMEOH) is proposed by which a number of differently sized squares on a page can be indexed efficiently.

Gholam A et al. (2015) [24], introduces two novel methods as image descriptors. First method is based on feature extraction using scale invariant feature transform (SIFT) algorithm. On the extracted features, k-means clustering is applied, and then dimensionality reductions are applied which makes SIFT features more efficient and realistic for image retrieval problem. Using the proposed approach along with benefits of SIFT features, memory storage is also decreased. The second method is based on color auto-correlogram and wavelet transform to extract the features. As a result, our first retrieval system using SIFT and k-means is fast and accurate. It can also able manage large databases efficiently.

3.2 SIMILARITY MATCHING

Instead of exact matching, CBIR calculates the visual similarity between a query image and images in database. Based on this similarity measures output of CBIR system is not a single image, but it is the list of images. Many similarity measures have been developed for image retrieval some of them are Minkowski-Form distance, Quadratic Form (QF) distance etc. It forms the search part of the CBIR [1][2][3].

Chahooki M (2012) [25], uses dissimilarities of contour and region-based shape retrieval methods which results in more retrieval accuracy. It is supposed that the combination of two categories of shape description gives significant improvement in retrieval performance. The study proposes a new feature vector to coincide semantic and Euclidean distances. To achieve this, the chosen topological manifold is learnt by a distance-driven non-linear feature extraction method. From the experimental results, it can be seen that geometrical distances between the samples on the manifold space are more related to their semantic distance.

Anuja K et al. (2014) [26], propose content based image retrieval system reduce semantic gap and provides highly accurate, efficient and effective image retrieval result. Ontology is an inner body of knowledge which enfolds representations and descriptions of types of objects found in the domain. Here, core semantic multiple ontology is a used which combine ontologies such as feature ontology, semantic feature ontology, user ontology and metadata ontology for improving accuracy of feature matching.

Nishant S et al. (2014) [27], presents a novel technique for image retrieval based on selective regions matching using region codes. All images in the database are equally divided into number of regions. For each region a 4-bit region code is assigned depending on its relative location to the central region. Then, from these regions Dominant color and Local Binary Pattern (LBP) based texture features are extracted. Feature vectors together and their region codes are further stored and indexed in the database. Feature vectors of regions having similar region codes to the query image region are used for comparison.

Seetharaman K et al. (2014) [28], proposes a CBIR method, which is based on an efficient combination of multi-resolution based color and texture features. It considers color auto-correlogram of the hue (H) and saturation(s) components of HSV color space for color features, and value (V) component of HSV color space for texture features. These two features are calculated by using co-occurrence matrix at optimum level. It also contains a few dominant wavelet coefficients. The efficiency of the proposed system is tested with standard image databases, which show the proposed method achieves better accuracy and fast retrieval.

Mostafa R et al. (2015) [29], proposed a content-based image retrieval (CBIR) system based on intra-class and inter-class features. Intra-class features are a new layout for color distribution of an image based on the concept of co-occurrence matrix in RGB color space called as Distribution of Color Ton (DCT). Inter-class features are extracted using dual-tree complex wavelet transform, singular value decomposition (SVD), and conceptual segmentation based on human vision system. The system developed by this method has many advantages like choosing and extracting the appropriate visual feature, low complexity of feature extraction method, rich feature vector for image describing, proper use of SOM as classifier, simple similarity measures, low complexity and high accuracy.

3.3 INDEXING/RANKING:

Indexing is a technique to efficiently retrieve images from the image database based on feature extracted. Traditionally indexing is achieved manually by assigning descriptive metadata in the form of keywords or classification codes to each image and then uses this keyword for image retrieval. Again manual indexation suffered from complexity and subjectivity. Effective indexing and fast searching of images based on the visual features become an important issue in field of CBIR. As feature vectors of images have high dimensionality, indexing is achieved by the dimension reduction. Commonly used technique for dimension reduction is PCA (principal component analysis), some researchers also use KL (Karhunen-Loeve) transform. For multi-dimension data reduction R-trees, R*-trees, grid files are used [1][2[3].

Sibendu S et al. (2012) [30] presented directional line edge binary pattern (DLEBP) for texture image retrieval application. DLEBP extracts line edge information as well as eight directional line edge values from images. The experimental results show significantly improvement in terms of ARR as compared to other existing methods.

Lingyang C et al. (2013) [31], propose a rotation invariant PDIR method, which improves the image retrieval performances by exploiting the group spatial consistency of visual word matches. It first propose the Combined-Orientation-Position (COP) consistency to softly quantize the relative spatial relationship between visual word matches in a rotation invariant way; then embed the COP consistency into a simple consistency graph model to efficiently find the group of most consistent visual words. The high descriptive power of the COP consistency and the noise-proof property of the spatially consistent feature group enables to accurately match the visual words between partial duplicate images, which is effective in alleviating the influences of over-domination, random rotations, scale changes and slight affine transformations.

Bin Xu et al. (2015) [32], propose the Efficient Manifold Ranking algorithm to prolong the original manifold ranking scheme. This algorithm overcomes the limitation of traditional MR like scalable graph construction and efficient ranking computation. It uses an anchor graph on the database to design a new form of adjacency matrix used to speed up the ranking. Experimental results on large scale image databases show that EMR is a hopeful method for real world retrieval applications. Thus EMR proved a promising method for real world retrieval applications.

Daniel C et al. (2014) [33], present a novel approach for the re-ranking problem. It relies on the similarity of top-k lists produced by efficient indexing structures, rather than considering the distance information from the whole collection. With many indexing structures, wide experiments are conducted on a large image collection. Rigorous experimentation result shows that the proposed method can obtain significant effectiveness and, at the same time, efficiency is improved considerably.

Jun Y et al. (2015) [34], propose a novel ranking model based on the learning to rank framework. Specifically, it is based on large margin structured output learning. Here, the visual consistency is combined with the click features through a hypergraph regularizer term. In accordance with the fast alternating linearization method, a novel algorithm is stated which alternately minimizes two different approximations of the original objective function by keeping one function unchanged and linearizing the other.

Ko-Jen H et al. (2015) [35], propose a novel algorithm that combines the Pareto front method (PFM) and efficient manifold ranking (EMR) for multiple query image retrieval. Based on ranking generated by EMR, it creates Pareto points, which correspond to dissimilarities between a sample and every query. Then, sets of Pareto-optimal points, Pareto fronts, are computed. The second Pareto front (depth two) is obtained by removing the first Pareto front, and finding the non-dominated points among the remaining samples. It is repeated until the computed Pareto fronts contain enough samples to return to the user, or all samples are exhausted. The experimentation proves that the Pareto approach is better than linear combinations of ranking results.

Eleftherios T et al. (2015) [36], propose a scheme based on high dimensional image descriptor vectors, by assigning the value cardinalities of their dimensions. The dimensions value cardinalities describe the number of discrete values in the dimensions. The value cardinalities considerably may change significantly with different extraction methods. However, different quantization and normalization techniques have a strong impact on extraction process. Then multiple sort algorithms is used to reorder the descriptors' dimensions according to their value cardinalities, which will increase the probability of two similar images to lie within a close constant range.

3.4 RELEVANCE FEEDBACK

It governs the display of the outcomes, and the type of the user-interaction with possibility of refining the search through some automatic or manual preference (weighting) scheme, etc.Relevance feedback (RF) is useful measure to fill the semantic gap between low-level features and high level (semantic) features [1][2][3][4]. It is supervise active learning technique used to improve the effectiveness of the information system.

Zhongmiao X et al. (2014) [37], propose a complementary relevance feedback-based CBIR system which reduces the gap between short-term and long-term learning techniques to improve the retrieval performance. Specifically, it constructs an adaptive semantic repository in long-term learning to store retrieval patterns of historical query sessions. Then high-level semantic features from the semantic repository are extracted and seamlessly integrate low-level visual features and high-level semantic features. The high-level semantic features are dynamically updated based on users' query concept and therefore represent the image's semantic concept more accurately.

Barrena M et al. (2015) [5] develop Quatrisi Manager which describes the main issue in the field of CBIR system, the semantic gap. Based on color, texture and shape features the system provides a broad range of useful operations to facilitate the storage, management, retrieval and browsing of large image collections. Local and remote image loading processes enable the population of image collections. Further classification methods allow users to organize the collections according to their own interests. A multidimensional access method contributes to produce efficiency in similarity searches. Further parameterized similarity functions are used to give flexibility to the search by content processes.

Laxmi et al. (2015) [38] come up with a long-term learning scheme in relevance feedback for CBIR. They proposed a system integrates the user feedback from all iterations and instills memory into the feedback system of CBIR without saving any log of earlier retrievals. Here they use a method to update the cluster parameters and weights assigned to features by accumulating the knowledge obtained from the user over iterations. Experiment conducted using this approach leads to better convergence and thereby reduced number of iterations to achieve better retrieval accuracy.

Malay K. et al. (2015) [39], builds a system using the Multi-scale Geometric Analysis (MGA) of Non-Subsampled Contourlet Transform (NSCT).It adds Relevance Feedback (RF) mechanism to improve the retrieval performance and reduce the semantic gap. System uses a graph-theoretic approach to rank the images along with the user's feedback. First, a graph of images is constructed with edges reflecting the similarity of pairs of images with respect to the proposed feature representation. Then, images are ranked at each feedback round in terms of the probability that a random walk on this graph reaches an image tagged as relevant by the user before hitting a non-relevant one.

Aun I. et al. (2015) [40], proposed a semantic image retrieval system which incorporates Genetic algorithms with support vector machine and user feedback for image retrieval purposes. The method introduced new phenomena of feature extraction, in which the features are extracted through the Wavelet packets tree, and are fused, with the Eigen values of the Gabor filter. It assures the effective retrieval and sharing of images by taking the users considerations into an account.

4. COMPARATIVE ANALYSIS OF SOME RECENT TECHNIQUES

S. No.	Authors and Year	Technique used for feature extraction/ indexing/ matching / relevance feedback/ database used	Comments
1	M.A.Z. Chahooki, N.M. Charkari, 2012 [25]	• Shape based indexing : contour-based (Centroid and Farthest)and region based (squared and Zernike) method • Manifold learning is used for dimension reduction • MPEG-7 part B and fish shape dataset	• Retrieval accuracy is increased due to combination of four different characteristics of shape • Isomap manifold learning method increase the retrieval precision
2	Eleftherios Tiakas, Dimitrios Rafailidis, Anastasios Dimou, and Petros Daras, 2013 [36]	• Multi-sort indexing (MSINX) for high dimensional image descriptor • ImageClef Wikipedia Retrieval 2010, Flickr 1 M, IRISA datasets	• System is capable of performing accurate retrieval in low time • Mean average precision is calculated • It can handle dynamic operations of insertion and deletion in real time
3	Michal Batko, Jan Botorek, Petra Budikova, Pavel Zezula, 2013 [12]	• Automatic image annotation and classification (semantic search) • Profimedia photo bank and profimedia search log • Annotation precision and response time is calculated	• Focused on web annotation • Combines image and text processing techniques • Annotation quality can be significantly improve due to various expansion and reduction techniques used
4	Romain Raveaux, Jean-Christophe Burie, Jean-Marc Ogier, 2013 [16]	• Image is segmented into regions. • Graph based image representation (region adjacency graph) is calculated to show spatial relationship • From each region color (color histogram), texture (co-occurrence matrices) and shape (Zernike Moments) features are computed • K-means clustering is used to cluster regions • Coil-100 dataset is used.	• This approach gives good results as compare to tree based approach • Structural approach requires fewer number of words to reach its best performance
5	Lingyang Chu, Shuqiang Jiang, Shuhui Wang, Yanyan Zhang, Qingming Huang, 2013[31]	• Partial Duplicate Image Retrieval (PDIR) using SIFT features • Combined orientation position (COP) consistency Graph model for similarity matching • Mean Average Precision (MAP) and Average Retrieval Time (ART) is calculated. • Uses Holodays/1000k, Sub-Dupimage/1000k, Dupimage1000k, IPDID/1000k and mobile data set	• It enable to accurately match visual words between partial duplicate images • As PDIR has only one system parameter, it improves robustness in dealing with different data, as it based on SIFT feature extraction. • Method proves effective in retrieving near duplicate images.
6	SibenduSamanta, R. P. Maheshwari, ManojTripathy, 2013 [30]	• Image indexing and retrieval using Line Edge Binary Pattern (LEBP) • Brodatz image dataset • Performance is measured using Average Retrieval Rate (ARR)	• DLEBP extract line edge information as well as eight directional line edge values • Image retrieval performance significantly improves in terms of Average retrieval rate (ARR)
7	Suraya Abu Bakar, Muhammad Suzuri Hitam, Wan Nural JawahirHj Wan Yussof, 2013 [22]	• Scale invariant feature transform (SIFT) based feature extraction • Experimentation done on MPEG-7, COIL-20 and ZuBuD dataset	• Mostly suited and provide excellent retrieval results for images with many corners • Good alternative to traditional CBIR system as it is invariant to scale, rotation and translation
8	Jaehyun An, Sang Hwa Lee, and Nam Ik Cho, 2014 [6]	• Descriptor based on color of salient objects • Binary map(spatial distribution of dominant color) roughly describes object shape and relative location • Testing is done on corel 1k and corel 10k dataset.	• Provide better retrieval performance than conventional color based methods • Binary map of dominant color matches the shapes well • Therefore mostly suitable for object-based color image retrieval

9	Zhiyong Cheng, Jialie Shen, Haiyan Miao, 2014 [13]	• Color (color histogram, color correlogram) and texture (Gabor, Tamura and Edge histogram) visual features • textual information (social-tag based) retrieval method • relevance feedback • NUS-WIDE and MIRFLICKR dataset	• Retrieval system using textual feature can achieve much better performance than only visual features
10	Hanwang Zhang, Zheng-Jun Zha, Yang Yang, Shuicheng Yan, Yue Gao, 2014 [14]	• Tries to reduce Semantic gap • Used Hybrid feedback mechanism to refine search result	• Method can characterize semantic resemblance among image accurately • User can search images quickly
11	Daniel Carlos, Guimarães Pedronette, Jurandy Almeida, Ricardo da S. Torres, 2014 [33]	• Image re-ranking using BP-tree, DBM-tree, M-tree and Slim-tree • Result (MAP) evaluated with different feature includes: ACC, BIC,CCV,GCH and LCH • ALOI dataset with 72000 images and 1000 classes of objects	• Rank list is produced by efficient indexing structure • it is scalable • Well suited to large dataset
12	Nishant Shrivastava, Vipin Tyagi, 2014 [27]	• Region based segmentation • Dominant color and local binary pattern (LBP) based feature extraction of each region • MPEG7 CCD and Corel image dataset • Average Normalized Modified Retrieval Rank (ANMRR) is employed to evaluate the performance	• ROI also used to specify spatial locations of regions • It improves efficiency through features set containing a dominant color and LBP • It also consumes less computation time
13	Emir Sokic, Samim Konjicija, 2014 [17]	• Fourier descriptor based feature extraction • MPEG-7 CE-1 set B, Swedish leaf dataset is used.	• Method outperforms both in effectiveness and efficiency • Not suitable for region based approaches. • This descriptor is essentially a contour based
14	K. Seetharaman, M. Kamarasan, 2014 [28]	• Multi-resolution (color and texture) based features extraction • Vistex texture DB and Brodatz texture image dataset is used. • Average precision and recall rate is calculated.	• System is conceptually simple and memory efficient • It reduces the computational complexity • Desirable for large size image database
15	Zhongmiao Xiao, Xiaojun Qi, 2014 [37]	• Relevance feedback • Combines High level semantic and low level visual features • Datasets used are: COREL images, Flickr Images, NUS-WIDE images	• It exploits synergism between short term and long term learning technique to overcome weakness of individual learning
16	Ahmad Alzu'bi, Abbes Amira, Naeem Ramzan, 2015 [4]	• Sematic image retrieval to reduce semantic gap is discussed. • Various relevance feedback scheme are explained.	• Affect the performance of system in terms of accuracy, speed is discussed.
17	Cong Bai, Jinglin Zhang, Zhi Liu, Wan-Lei Zhao, 2015 [18]	• Multiresolution feature vector are created using Color and texture features • K-means histogram for classification of number of histogram bins. • Widely used texture databases are selected: VisTex, A LOT and Stex	• Easy implementation • Improves retrieval performance compare to state-of –art techniques.
18	A. Laxmi, Malay Nema and Subrata Rakshit, 2015 [38]	• Relevance feedback by axis re-weighting scheme is proposed • Caltech and corel dataset is used for testing	• Approach leads to better convergence • reduces number of iterations required to achieve better retrieval accuracy
19	Alex Papushoy, Adrian G. Bors, 2015 [15]	• Defining salient regions at local and global level • Earth movers distance (EMD) is used for similarity comparison • Benchmark dataset: SIMPLIcity and Corel 1K	• Method outperforms using visual attention

			• produces comparable results to relevance feedback based retrieval system • provides consistent results for large variety of image categories
20	Izem Hamouchenel, Saliha Aouat, 2015 [8]	• Texture segmentation using neighbors based binary pattern (NBP) method • Brodatz dataset is used.	• Research textures have been well recognized, Produces better segmentation results compare to classical decomposition method • Improve accuracy of segmentation.
21	M. Barrena, A. Caro, M. L. Durán, P. G. Rodríguez, J. P. Arias-Nicolás, T Alonso, 2015 [5]	• Color, texture and shapes feature extraction • Classification using automated learning • Indexing and relevance feedback is used to increase the retrieval performance	• Three spaces in combination improve results for recall and precision • Relevance feedback enhance quality of retrieval process • Query finding are listed and sorted
22	Shaoyan Sun, Wengang Zhou, Qi Tian, and Houqiang Li, 2015 [9]	• Region identification with generic object detection • Fusion of CNN (Convolutional Neural Network) and VLAD (Vector of Locally Aggregated Descriptors) features • Benchmark dataset: Holidays and UKBench dataset	• Promising accuracy is achieved • System developed is scalable • Image representation is efficient in memory overhead • Retrieval process is time efficient
23	Anu Bala , Tajinder Kaur, 2015 [19]	• Local texton XOR patterns feature descriptor • Corel dataset is used in experimentation.	• Feature vector is constructed based on LTxXORPs and HSV histogram • Shows significant improvement in terms of Recall and Precision
24	Yusuke Matsui, Kiyoharu Aizawa, Yushi Jing, 2015 [23]	• Fine multi-scale edge orientation histogram based feature extraction is proposed. • Magna dataset is used for comparision	• Proposed good solution to sketch based image retrieval • Could retrieval images from MANGA database (not for other sketches)
25	Anuja Khodaskar , Siddarth Ladhake, 2015 [26]	• CBIR system using Ontology • Tries to reduce Semantic Gap using shared vocabulary(semantic features)	• Bridges the semantic gap between low and high level features • Improves semantic image retrieval with high accuracy, precision and recall
26	Mostafa Rahimi , Mohsen Ebrahimi Moghaddam, 2015 [29]	• Color ton distribution descriptors based on color co-occurrence matrices • Classification using self-organizing map • Corel and VisTex dataset	• It chooses and extracts appropriate visual features with rich contents • Low complexity of feature extraction method • Proper use of SOM as classifier • Can be used as structural and signal processing feature description • System fail to provide satisfactory result in image with intense color distribution
27	Malay Kumar Kundu, Manish Chowdhury, Samuel Rota Bulo, 2015 [39]	• Feature extraction using Multi-scale geometric analysis (MGA) of non-subsampled contourlet transform (NSTC) • Graph based relevance feedback for ranking • SIMPLIcity dataset, OLIVA dataset and Caltech dataset is used for testing purpose.	• Reduces dimensionality of feature representation • User can process retrieval loop to reduce semantic gap • Ranking mechanism effectively exploits user’s feedback to improve quality of retrieval process
28	Aun Irtaza, M. Arfan Jaffar, Mannan Saeed Muhammad, 2015 [40]	• CBIR using Genetic Algorithm and SVM • Assures effective retrieval by taking users considerations into an account (i.e. Relevance feedback) • Corel set A, corel set B dataset	• Genetically optimized SVM overcomes limitations of regular SVM like classifier instability, hyperplane biasness • Image retrieval results shows superiority in terms of recall and precision

29	Bin Xu, Jiajun Bu, Chun Chen, Can Wang, Deng Cai, Xiaofei He,, 2015 [32]	• Feature extraction using Grid color moment, edge histogram, Gabor wavelets, local binary pattern and GIST features. • Graph based ranking is used • Experimentation on Corel and MNIST dataset	• Supports scalable graph reconstruction • Significantly reduces the computational time • Feasible to large scale image retrieval system
30	Kommineni Jenni, Satria Mandala, Mohd Shahrizal Sunar, 2015 [10]	• Color string coding and string comparison based feature extraction • SVM as classifier • Corel photo collection is used.	• Decreases computational complexity • Significantly increase accuracy in image retrieval
31	Jun Yu, Dacheng Tao, Meng Wang, Yong Rui,2015 [34]	• Visual features (color, shape and texture) extraction • Users feedback • Dataset is collected from Microsoft Bing image search engine.	• More accurate and robust ranking model is designed • Noises in clicked features can be removed by visual contents
32	Gholam Ali Montazer, Davar Giveki,2015 [24]	• Scale invariant feature transform (SIFT) based feature extraction • K-means clustering algorithm for classification • Tested on Caltech 101 dataset	• Using k-means clustering two main drawbacks of sift i.e. memory usage and matching time is overcome • Shows high performance in searching images with object in them • Needs more improvement for complex image (scene)
33	Jing-Ming Guo, Heri Prasetyo, and Jen-Ho Chen,2015 [20]	• Feature extraction based on Error Diffusion Block Truncation Coding (EDBTC) • Feature vectors are calculated using color histogram feature (CHF) and bit pattern histogram features (BHF) • Vector quantization is used to compute image feature descriptor • APR is calculated for corel 1000 and corel 10000 dataset	• Method is superior that former BTC methods • Due to added indexing scheme it achieves higher retrieval accuracy • Feature vector are computed by incorporating vector quantization
34	Min Huang, Huazhong Shu, Yaqiong Ma, Qiuping Gong, 2015 [21]	• Color moment (color), Zernike moments(Shape) and co-occurrence matrix (texture) based feature extraction • Corel image dataset	• Combination of three features solve shortcoming (i.e. partly express and description of image) of method using single feature • Retrieval result is better • Contrary retrieval time will increased
35	Menglin Liu, Li Yang, Yanmei Liang, 2015 [11]	• Feature extraction based on (Chroma) color and (gray color co-occurrence matrices, tamura and wavelet) texture features	• Gives better performance with traditional luminance texture images
36	Ko-Jen Hsiao, Jeff Calder, Alfred O. Hero, 2015 [35]	• Pareto front method with (efficient manifold ranking) EMR • Able to handle multiple query with the queries belongs to different image semantics.	• result is better than linear combination of ranking results • suitable for real-world datasets

5. DISCUSSIONS

The main points extracted from exhaustive survey are as follows:

- Color, shape and texture are widely used low-level features to represent the content of an image. Although CBIR systems using single feature are available, contents of image can be more accurately represented by using multiple features. Recent CBIR system mostly uses combination of these low-level features. This technique proves more effective than using a single feature.
- Though low-level features are good to represent image contents, they lead to number of mismatches in result. Therefore semantic (high level) aspects of images are used in combination of these low-level features. Semantic features are mostly obtained from textual annotation. Automatic image annotation method [22] is also proposed to develop CBIR system. Defining vocabulary and language to describe the different parts of the picture are still a very challenging task for both image processing and CBIR communities.
- The semantic gap refers to the gap between the outcome of the automatic feature based analysis and the user's interpretation (i.e. gap between low-level and high-level

features). Semantic gap results in large number of mismatches (irrelevant image) in response to input query. To reduce this semantic gap to give more accurate and relevant result always a challenging task.

- Some standards like MPEG-7 feature descriptors, Scale Invariant Feature Transform (SIFT) are developed. These standard descriptors are highly redundant and reduce complexity of applications. They are also drawn interest of many researchers.
- Similarity matching is used to produce the output by comparing feature vectors of images. As CBIR system uses similarity matching, the output contains set of similar images. Because of high dimensional resultant feature vector, it is again challenging area of research.
- Indexing or ranking of image based on the feature extracted is also important area of research. High dimensionality is of one of the important problems in CBIR due to possible size of feature space and images. Therefore, dimension reduction is necessary to improve the efficiency of the retrieval task.
- Some CBIR systems used relevance feedback mechanism as a user interface. It helps to design interactive CBIR systems. It enables to customize the output to fit user's specific query.

6. CONCLUSIONS AND FUTURE SCOPE

This paper has presented a comprehensive survey on different techniques and recent research works in the CBIR system. It includes study and discussions of general retrieval framework which most of CBIR systems have adopted over the past years. It further summarizes important points extracted from extensive survey. The survey proves that CBIR is still a promising area of research. A lot of work is undergoing in this area to develop more accurate and efficient content based image retrieval system. Reducing the gap between low-level and high-level features, indexing (ranking), Combining different features extraction methods, relevance feedback are some open areas of research. More work can also be needed to optimize retrieval performance. Instead of working on single area, most recent CBIR systems work with two or more areas simultaneously this always leads to better results in terms of performance.

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