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Review Paper

Use of Low Level Features for Content Based Image Retrieval: Survey

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Abstract

Survey paper reviews the fundamental theories of Content Based Image Retrieval algorithms and development in this field. These algorithms retrieve the digital images from large image database. Image is retrieved from the low level visual content features of query image that is color, texture, shape and spatial location. First we review the visual content description of image and then the fundamental schemes for content based image retrieval are discussed. We also address the comparison of query image and target image of large data base with the indexing scheme to retrieve the image. Relevance feedback in CBIR system is a dominant technique for the retrieval of image which is derived from user's feedback iteration process. Lastly we discuss the evaluation and semantic gap. In the concluding section we mention our views on role of similarity function with learning and interaction, the problem of evaluation and semantic gap as well as future research directions.

Keywords: Image retrieval, dominant color, grey level co-occurrence matrix, gradient vector flow field.

Introduction

The term CBIR can be defined as to retrieve the image from low level features like texture, shape spatial information or color[1]. In early era of this emerging filed the image was retrieved by text description called as Text Based Image Retrieval [TBIR]. Complete surveys of this technique can be viewed in Chang S.K. and Hsu A.[2]. All text based image retrieval systems require the text description with images in large scale data bases and manually this task is not feasible. As a result, text based image retrieval systems were not applicable for task dependent queries[3]. Image retrieval process can be visualized as in figure-1.

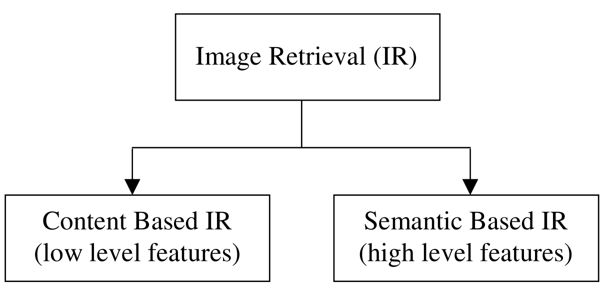

Figure-1
Image Retrieval Process

The tricky feature of CBIR is to minimize the difference of content based features and semantic based features[4].

Content Based Image Retrieval

Content based visual features are categorized into two domains; Common visual contents and Field Specific visual contents like face recognition, task dependent applications etc[5]. On the other hand, high level features include semantic based image retrieval computed from text description or by complex algorithms of visual contents[6]. The mixture of these content based features is required for better retrieval of image according to the application[7]. The most important challenge of CBIR system is to determine the exact/approximate matching image of database to the query image. Relevance feedback techniques have been introduced to produce efficient query results by reducing the comparison difference of content and semantic visual features[8]. Few CBIR systems used global color and texture features whereas few used local color and texture features for better retrieval efficiency[9]. Later the idea of segmentation of image on the basis of region has been proposed called as Region Based Image Retrieval (RBIR) and shows better result performance[10].

Color: Color is a dominant and distinguishable feature for image retrieval. Mostly CBIR systems use color space, histogram, moments, color coherence vector and dominant color descriptor to represent color[4]. The invariant features of color have been proposed for CBIR system recently. Invariant color features are commuted on the basis of Schafer model and produce the results like brightness and geometry view when used for image retrieval process[11]. However in parallel they also decrease the discrimination power of images[12].

Color Space: Color space consists of three dimensional spaces and color is used as a vector in it. Color Spaces are required for description of color based retrieval of image[13]. Mostly RGB, LAB, LUV, HSV, YCrCb and opponent color space are used. The selection of color space is done from uniformity characteristics[14] and uniformity means to have colors points having similar distance in color space as perceived by human eye.

Color Histogram

It is a standard demonstration of color characteristic in CBIR systems[15]. It is very efficient in description of both local and global features of colors[16]. It computes the chromatic information and invariant of image along the view axes for translation and rotation[17]. When the large scale image data base computes histogram, its efficiency is not satisfactory. To overcome this conflict joint histogram technique is introduced[18]. Color histogram is a fundamental technique for retrieving images and extensively used in CBIR systems. Color space has segmentation; for every segment the color pixels within its bandwidth are counted which shows the relative frequencies of counted colors. We use RGB color space for the histograms.

Color Coherence Vector: Color coherence vector is present in unique style and due to extra information of spatial locations as compared to histogram; results prove to be more effectivec[19].

Dominant Color Descriptor
It consists of two sections; Color vectors (Cv) and Percentage (fi). Color vector is extracted from Y "C'r domain which describes the color characteristics and percentage defines the fraction of prevailing color in the image. Table 1 shows the work done regarding use of color features in order to retrieve the image.

Table-1
Color features for retrieval of image

Color features	Advantages	Limitations	Results
Color Space13[13, 20]	Each pixel of image is represented in 3D space and widely used for digital image display	Cannot isolate the brightness information that is more sensitive to human eye.	Color difference perceived by human between color spaces forms Euclidean distance.
Color Moments[21]	They are compact features of color and sensitive to spatial information.	Due to compactness, may have low power discrimination.	Successfully used in CBIR systems.
Color Histogram[22]	Extracts both local and global features of colors and invariant to any transformation.	Decreases the performance when used with large number of bins.	Histogram would get saturated with large number of database images.
Color Coherence Vector[19]	More efficient results due to additive spatial information.	Complex enough due to its high dimensionality.	Provides efficient results with uniform color space.

Texture: In computer vision texture feature is defined as a description of local shape and color feature or in a more comprehensive way it is defined as structure and randomness[23]. Structural methods consist of graphical method which tends to be more effective when applied to the texture[24]. Randomness methods represent Tamura features, Wold composition, Markov random field, wavelet transform, dual tree complex wavelet and contour lets. Texture can be represented by Grey Level Co-occurrence [9]. Texture is an essential feature for general images but its comprehensive definition does not exist still yet.

Tamura Features

Tamura features have six characteristics which are contrast, coarseness, line-likeness, regularity, roughness and directionality[23]. Initial three characteristics proved to be noteworthy in CBIR systems such as QBIC[25]. Coarseness is defined as a texture granularity, contrast is computed from statistical methods of moment invariants such as kurtosis and variance of the entire image and directionality is computed from convolution of images[26].

Simultaneous Auto Regressive (SAR) Model

Another important representation of texture is a scale simultaneous auto regressive (SAR) model. It describes that when a deterministic dynamic system is subject to observation noise and state, it results in texture[27]. Other models use statistical analysis for texture[28].

Gabor Filter Features

These filters have been commonly used to retrieve images in the shape of texture [29]. Gabor filters are appropriate to reduce the joint ambiguity issue in space and frequency domains and used as tuned and scaled edge detector [16].

Wavelet Transform Features

Wavelets have become noteworthy recently. Its significant features are locality and compression of query images[30].

Contour let Transform

It has two distinct and consecutive breakdown stages; multi scale disintegration and directional disintegration. First multi scale disintegration applies Laplacian pyramid method to transform the image into one coarse version. Secondly a directional stage uses iteratively two dimensional filtering and critical down sampling to partition each LP into flexible number of frequency wedge-shaped sub-bands thus capturing geometric structures and directional information in real-world images. Table 2 lists use of texture features for retrieval of image.

Table-2
Texture features for image retrieval

Texture features	Advantages	Limitations	Results
Tamura [23]	Combination of color histogram and tamura provides effective results.	Highly complex computational method to extract image.	Used in CBIR systems like photo book, QBIC.
Gabor filter [29]	Used as edge and line detector to detect different frequency and orientation.	Mainly effective for manmade objects only.	Uncertainty in space is minimized thus providing good results.
Wavelet transform [30]	Wavelet filters with salient point features are efficient for retrieval of image.	The general selection of wavelet filter is dangerous for investigation.	Results in a multi resolution approach to texture features.

Shape

Local shapes feature extracts geometric details of image[31]. Shape features of image object have extensive application in CBIR systems. Apart from the features of texture and color, the features of shape can be calculated once the segmentation process of image is done[32]. A superior shape feature of object image is the one which is translation invariant, rotation invariant and scaling invariant along the axis. Shape features tend to be efficient in specific applications such as manmade objects[33]. i. Shape retrieval: probing for all same objects in a typically large database of images that are same with respect to the query. Normally all shape object images in database have distance function computed for the query shape. ii. Shape identification and representation: describe whether the shape images with the given query images are similar or not. iii. Shape arrangement and listing: converting or translating one shape image whole or a part of it into one of the most similar shape image. iv. Shape estimation and simplification: making a shape image features of fewer like (points, segments, triangles, etc.), which are alike to query image.

The schemes for shape explanation are classified into edged based rectilinear shapes, polygonal estimation and Fourier based shape descriptors[34-36]. Shape features can be represented by circularity, peculiarity, Fourier descriptors, moment invariants, and one dimensional function for shape representation etc.[36-37]. Gradient Vector flow techniques are also used for shape feature extraction[10]. In the following sections we briefly address few shape features which have extensive application in CBIR systems. Intensity information and local shape are mentioned for invariant method of object retrieval[23]. It is composed of complete family of differential affine invariant descriptors geometric invariants.

Peculiarity and Major Axis Orientation

The major axis orientation is explained as unit vector for the second order covariance matrix of large calculated eigen value of an object. Fraction of small eigen value to large eigen value is defined as peculiarity [38]. Table 3 summarizes the use of shape features for image retrieval.

Table-3
Image retrieval by using image shape features

Shape features	Advantages	Limitations	Results
Fourier descriptor [36, 39]	Fast Fourier transformation can also be used for efficient results	The DC coefficient is dependent on the position of a shape and hence discarded	Rotation, scale and translation invariants results are computed
Eccentricity and axis orientation [38]	Increased the user interaction for meaningful efficiency of shape features	Higher values of it show the elliptical shape which has complex computational method	Efficient and faster retrievals results

Spatial Location

Spatial location is also significant and used for region segmentation. Spatial location is described as top/bottom, top left/right and back/front as per the position of object in an image like sea and sky may have same characteristics of texture and color but the spatial information is unlike. Sky typically represents the above portion whereas sea is at the below portion of an image. Hence the spatial information of multiple objects in an image extracts significant information for retrieval of images. Mostly spatial information is presented in terms of 2D strings[40]. Spatial locations are represented as 2D string and variant. And it also describes the interaction of regions. The 2D G-string divides the object of image with object's least bounding envelope and increases the spatial interaction in two sets. Therefore, 2D C-string is introduced to reduce the segmentation process[41]. 2D-B string describes an object with two signs, position of beginning and edge of the object[42]. The 2D string spatial quad-tree is used for spatial information representation[43].

Distance Function Interpretation and Filtering

Distance Measure between Features: The data of images is stored as a feature vector in feature spaces and then they get compared using a comparison function. Most similar images are retrieved through content based image retrieval process[44]. The high quality evaluation technique computes shape features after segmentation of regions of image[45]. Comparing a query and object in vector space is computed from elastic comparison[46]. Scale spaces comparisons are calculated on the basis of contour via smoothing process[22].

Minkowski Distance: Minkowski distances have been used in color histogram. For measuring the distance function of two images minkowski distance technique is most widely used[47]. MARS system used Euclidean distance function technique to calculate comparison of texture features[48]. Euclidean distance is used for color and shape features in NETRA CBIR[49].

Quadratic Form (QF) Distance: The Minkowski distance is used for histogram only and does not explain its bins which specify the features of histogram. As a result of this, quadratic form distance has been proposed. Color histogram based image retrieval system uses QF distance [50]. QF distance tends to have better and efficient performance on the basis of cross matching among colors as compared to Euclidean distance function and histogram intersection [51].

Mahalanobis Distance: The Mahalanobis distance technique is specifically used when features are linearly dependent[52]. The color, texture and shape features described salient features of the query. Comparison of feature values measured with feeble cutting having a Mahalanobis distance function calculates the distance of feature vectors which are combination of texture, position, eccentricity, area, direction and color of the two ellipses [53]. Salient image features are stored in histogram on the basis of color on the inside and outside etc. Matching process is done on the basis of most similar point features[54].

Filtering Phases: Image retrieval is composed of two phases. First phase is done with partial filtering. Second phase performs entire distance function process on images with filtering i.e., indexing.

Indexing Schemes: Before applying the indexing schemes dimension reduction is done[55]. However, recent researches result that basically not any indexing technique provides good results simultaneously on low and high dimensional data[56]. This is called "curse of dimensionality"; this is a process in which indexing techniques results are poor because of increasing dimensionality[8]. The R*-trees results get reduced as the dimensions size increases[57]. Principal Component Analysis (PCA) is used for decrease of dimension. It is appropriate for features set of a vector space such that there are variant axes with respect to the data variation[58]. The PCA technique has been used in QBIC for reducing the dimension of feature vectors. Apart from PCA, neural network technique is also used for dimension reduction[59]. Later than dimension reduction, indexing schemes are applied. Variety of schemes have been introduced for dimension lessening like s R-tree (particularly, R*-tree, linear quad-trees, K-d-B tree) and grid file[60-63].

Region tree is a multidimensional index and can be defined[64]: i. In multiple dimensions it behaves like B-tree, ii. R*-tree is sensitive to overflow and retakes data set, iii. Can be used for low dimensional features (texture, shape, color), iv. Dimension reduction from high dimensional features to low dimensions, v. Overlapping regions with query region must be searched, vi. A matrix for generation of combined index based on color, shape and relevance feedback is discussed[65]. The authors have devised a new mechanism based on three different techniques which resulted in a unique descriptor used to store images in the database. Results of experiments have shown that the images are retrieved from the database efficiently and accurately.

Majority of multidimensional indexing techniques show significant result for low dimensions but the results degrade rapidly as the dimensions increase[65]. Therefore, the Pyramid–Technique has been introduced which divides the space into 2 dimensions[34]. After that it further cuts the pyramids into a number of blocks. Three commonly known classes of indexing methods have been categorized and discussed that are used in large image databases. They are space segmentation, data segmentation and distance based segmentation techniques and briefly discussed below[66-68]. i. In space segmentation, the data set has been ordered like an R- tree[66]. The node of tree behaves like region in this space. When nodes in a region exceed to a given value, the region gets partitioned into sub regions and becomes the derived region of node containing the based region[69]. A further enhancement in technique is done by the k-d B-tree which is a multidimensional index. It is data structure with equal complexity (logN) from base to up growing dimension[70]. ii. Data segmentation scheme represents every data set in feature vector space[67]. The SS-tree and SR-tree have used the point of intersection of two curves that is hyper sphere and hyper rectangle of the smallest bounding as a bounding object of a dataset[67]. As dimension increases, it mixes up with a one bounding region. iii. Distance based technique is query dependent space segmentation technique. Fundamental practice is to select the data set and divide the feature space into groups[68]. For high dimensional feature vectors the VP-tree has been introduced[71]. M-tree is proposed which is an indexing strategy used for triangle inequality of metric spaces[72].

User Interaction

Interaction of users in CBIR system is of vital worth[73]. User interaction in CBIR system consists of a query formation which is discussed briefly below.

Category Browsing: Category browsing searches the image in database with the category specified for query[74]. Categorizing and fast browsing can be done with self-organizing scheme which carries clustering or alignment of same regions of images[75]. The self-organizing image browsing maps is a continuous valued vector which extracts color space and texture features of image.

Query by Example: User gives example of image in query by example to facilitate the system for the retrieval process. CBIR system extracts the features from example image[76]. Then database is searched for the most similar feature image. In query by example it is not mandatory for the user to give description of image in any form. In Web based browsing engines the user provides categories like object description in the required spatial order[77]. This algorithm is highly beneficial when query image is having same object with multiple viewing situations[11]. In some conditions, query by example cannot facilitate user to have exact image retrieved. For this the user gives some description of query image in text form[78]. Flaw of QBE is that it computes the result on the basis of first set of images. Searching for a set of initial images which must have one positive image can be challenging. This situation is called as "page zero problem"[75].

Query by Sketch: User sketches the image with characteristics of features (color, texture, shape) of query image with a graphic user interface tool to retrieve the image in query by sketch method[79]. Many times sketch is enough for the retrieval of images. Sketched outlines of object image have to be normalized for reducing the negative details of the query object before comparing it to database images[80].

Query by Group Example: Query by group example permits the user to give group images example of query to the system. The system will then search for exact or approximate images relevant to group image examples of query[79]. By using group by query example we can specify the target images features more accurately with different image example in group. Recently CBIR systems have both query examples (relevant and irrelevant). For both groups, the database is searched for group of relevant images stored in visual dictionary database [81].

Relevance Feedback: In current years, a wide research has been found in Content Based Image Retrieval (CBIR) area while using Relevance Feedback (RF) techniques for making better retrieval of images possible[6]. In relevance feedback systems, a searching interface animatedly changes the weights of content based visual features in the query image based on the user feedback of relevant retrieved images [82].

Relevance Feedback Schemes: There are various relevance feedback algorithms categorized on the basis of statistical analysis, kernel based approach techniques and entropy based techniques for relevance feedback [7].

Statistical based Techniques: Early research work was done by weight adjustments method. It uses same relevant images data set in vector space to get the improved results of cluster relevant examples [83]. These methods have a key advantage that under transformations the relevant images form groups in image database and the irrelevant images form detached[39]. The transformation has been done with relevance feedback algorithm [82].

Delta Mean Algorithm: The Delta Mean algorithm determines which features can efficiently differentiate between the relevant and irrelevant image examples [84].

Standard Deviation and Variance: Inverse variance and standard deviation methods show better results as compared to the delta mean because they are less constrained algorithms [85]. These methods combine the irrelevant and relevant images with no hypothesis about the nature of distribution of irrelevant images. These methods have created multi modal distributions in which CBIR system does not extract low level features in a proper way[8].

Kernel based Techniques: Relevance feedback is achieved while using some kernel based techniques. Parzel Window Based Density Estimation uses Bayesian inference for identifying images to mark as a relevant or irrelevant[86]. For this method the information of densities of relevant and irrelevant images are required. Parametric or non-parametric techniques are used to calculate these densities.

Bayesian Frame work: Textual based image retrieval method is used extensively in this scheme [67]. User interaction is always computed in terms of probabilities of a random variable. Generally, network consists of three steps: query image, feature index and relevant image.

Support Vector Machines: Recently for relevance feedback algorithms there is extensive use of SVMs [87] (Support Vector Machines). SVMs identify linearly in dissoluble classes on the basis of kernel. The main goal of an SVM is to calculate a hyper plane distance to the closest of point in relevant and irrelevant images and becomes maximized.

Biased Discriminant Analysis (BDA): In a CBIR system positive and negative image datasets are spread in feature space[82]. BDA calculates the linear transformation for the scattered negative and positive images.

Entropy Based Techniques: Entropy is the fraction of random variable deviation to randomness. The entropy of features data set of relevant images is calculated in weight adjustment technique[88]. Feature computes the group of relevant images and then entropy of features is decreased. Entropy is a very appealing technique as no hypothesis has to be considered on the distribution of random variable.

KL Distance: KL Distance or Divergence makes few difference measures on the basis of entropy due to which derivation of KL Distance calculated between two distributions is done [82]. Table 4 highlights Relevance Feedback methods in tabular form.

Other Techniques: The techniques described in the above section are only a few. Literature has a variety of relevance feedback algorithms. Many techniques exist between Decision Trees to Bayesian Estimation[27].

Table-4
Relevance Feedback Methods

	Relevance feedback methods	Advantages	Limitations
Category	Delta Mean algorithm[84]	Vital role of features. Efficiently separating positive and negative images.	As small size cannot calculate exact variance of data set, so it is receptive to data set size.
Statistical Based RF Methods	Inverse Sigma[85]	Bunch of relevant images exhibit the specific features and are inversely proportional to the relevant image set variance.	It assumed irrelevant sample to be unimodal which is not actually possible.
	QPM[89]	Estimates the perfect query point from which the ideal relevant images can be retrieved.	QPM have the hypothesis of unimodality on relevant samples and unable to make better use of irrelevant samples when images are not unimodal.
Kernel Based RF Methods	Bayesian Network[67]	It described the efficient information which imitates the human mind.	Performance evaluation using Bayesian models decreases considerably when extraction of texture, shape and color features is done individually for retrieval of image.
	SVM [90]	SVM derived better results for pattern identification without dealing with the filed information.	SVM respond less than other methods and sensitive to small sample data sizes.
	BDA[82]	For the nonlinear data it is transformed in inner product form.	Gaussian distribution methods for relevant data set are the main flaw for the efficient results.
Entropy Based Methods	KL Distance [82]	Variant features make this technique more effective for image retrieval.	Lacks the constraints on the distributions of data.

A survey of existing content based image retrieval techniques is presented [91]. The authors have highlighted different components involved in the image retrieval process like feature description, index generation, image storage and image retrieval based on unique index. About eighty plus papers have been discussed and the authors have concluded that image retrieval algorithms that have simple implementation and reasonable accuracy and efficiency are mostly adaptable and acceptable by different implementations.

System Evaluation: Image retrieval evaluation is an integral part for the high quality performance of CBIR systems and effective in many CBIR applications [92]. Two methods; recall and precision have been commonly used in the evaluation of CBIR systems[38]. Precision is given as relevant retrieved images ratio for the query and recall is relevant images fraction given by query. Assume q a query and D a data element[93]. Two sets are further formed from this data element: R (q) is the relevant images set for query q and $\bar{R}$(q) is the irrelevant images set. Assume that an image set A (q) is given back when a data element D receives a query q. Precision is defined as ratio of result images and relevant query image:

$$P=\frac{A(q)\cap R(q)}{A(q)}$$

Where as relevant images ratio returned by the query is termed as recall:

$$R=\frac{A(q)\cap R(q)}{R(q)}$$

Since there is a tradeoff between the above two methods, improving the performance of one will decrease the performance of second and vice versa. Often in retrieval systems, recall performance becomes high with increasing the number of retrieved images whereas same time precision performance tends to decrease. An ideal ordering of query q would be made available by the ideal database. Moreover, each image relevance measure will also be supplied by the ideal database. The ideal database will return the image given the same query q. [j-πj] specifies the image I(j) displacement between two orderings and weighted displacement is obtained by adding all displacements and weighted by related images:

$$W=\sum S(Ij)\ [j-\pi j]$$

Outputs of two databases are compared by the weighed displacement. In many situations such sequence is obtained with human and general image experiments. In context to the experimental experience that uses human images, a peculiarity exists between an entire system evaluation and a system portion.

Recently a new retrieval performance evaluation measure has been introduced which is average normalized modified retrieval rank (ANMRR). It is a combination of precision and recall to gain a one goal calculation[94]. With practical example which uses human perception, evaluation of part of system and complete system can be made. First, the system is evaluated on the basis of calculating the increased effectiveness which is derived from the database and also from social sciences well known techniques which are utilized for statistical study of data[27]. Secondly, fundamental accuracy of system performance is done by user interaction. Such technique is used in MPEG Video Group[94]. Two parameters for calculating the performance of CBIR system are found; one is efficiency which is strongly concerned with the speed of retrieval and second is effectiveness which emphasizes on the high accuracy of retrieval[95]. For efficient retrieval system, a technique has been introduced called “SPY-TEC” which extracts features from the images to improve the performance of retrieval[34].

A neural network based learning system using relevance feedback approach for enhanced image retrieval is presented[96]. The authors have proposed the decision tree implementation in a unique fashion which results in limited retrieval complexity thus enhancing the overall weight age of the system. Experimental results have shown that the proposed system is more efficient and reliable than existing algorithms of the same caliber.

Conclusion

We have discussed essential content based image retrieval process techniques together with explanation of low level features, distance function measurement, indexing schemes and user dealings with the help of feedback and system performance evaluation. Color, texture, shape and spatial information extract image information on the basis of content based features for the retrieval of image in CBIR system. Varieties of algorithms have been introduced to calculate the similarity/comparison of features with the aid of distance functions. This paper discussed few distance functions which are used most commonly. Once dimension reduction process is performed, indexing scheme is applied for further processing of retrieved image. On the other hand, images can be retrieved with the aid of user feedback query. User feedback is obtained in the form of relevant and irrelevant images.

Role of Data Base: CBIR evaluation faces the deficiency of a common database in order to attain systematic results for different extracted features. For different features and tasks in different databases, the retrieval system performance is determined to give error rates (leaving-one-out). Noticeably more than one feature can be combined to obtain better results but here the analysis is limited to single features based on the retrieval result. In future there is probably room for increasing correlation among database research and content based image retrieval research. Work for such correlation has already been done although suitable query specification selection, searching process in altering similarity function measure and high dimensional feature vector space competent search are a few problems which remain unanswered.

User Interaction: User feedback in the search process should be engaged in such a way so that the required rich context for image retrieval process can be provided. In start, interaction plays a vital role. Currently most CBIR systems perform query space initialization irrespective of associative search, category search or target search.

Problem of Evaluation: The evaluation of system performance is an essential step in CBIR systems. The comparison of different evaluation methods with same feature has been missing. This is due to objective difficulties where query interface is essential in most systems. The data set has great influence in the performance evaluation of CBIR system. The problem also lies in the inner correlation of large data. When smaller data sets which have interior feature element or group of elements are contained in a large data set, the essential retrieval difficulty lies in every data set instead of group of data set with the size of data set of one quarter. This is still an open issue except that the composition is generally agreed with the use of large data sets. All content based methods require significant attention for evaluation methods in future.

Semantic Gap: The goal of content based retrieval systems should be to minimize the difference/gap between the human perception semantics richness and available content based visual features. The approach to bridge this semantic gap is done from external information of image and integrating all sources of information about the query image. Image information can be obtained from different ways: image content, tagging the image, embedded text in image etc. Different techniques integrate image information to have specific images access.

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