Content-Based Image Retrieval Features: A Survey

Anum Masood
Department of Computer Science, COMSATS Institute of Information Technology, WahCantt, Pakistan
[E-mail: anum_msd21@yahoo.com]
Muhammad Alyas Shahid
Department of Computer Science, COMSATS Institute of Information Technology, WahCantt, Pakistan
[E-mail: mashahid79@gmail.com]
Muhammad Sharif
Department of Computer Science, COMSATS Institute of Information Technology, WahCantt, Pakistan
[E-mail: muhammadsharifmalik@yahoo.com]

ABSTRACT

Content-Based Image Retrieval (CBIR) systems have been used for the searching of relevant images in various research areas. In CBIR systems features such as shape, texture and color are used. The extraction of features is the main step on which the retrieval results depend. Color features in CBIR are used as in the color histogram, color moments, conventional color correlogram and color histogram. Color space selection is used to represent the information of color of the pixels of the query image. The shape is the basic characteristic of segmented regions of an image. Different methods are introduced for better retrieval using different shape representation techniques; earlier the global shape representations were used but with time moved towards local shape representations. The local shape is more related to the expressing of result instead of the method. Local shape features may be derived from the texture properties and the color derivatives. Texture features have been used for images of documents, segmentation-based recognition,and satellite images. Texture features are used in different CBIR systems along with color, shape, geometrical structure and sift features.

Keywords: **CBIR, Feature Extraction, Feature Selection, Color, Texture, Shape**

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I. INTRODUCTION:

With more digital applications, the number of images produced is increasing rapidly. Huge databases of images have to be searched to retrieve related images; this is mentioned as CBIR techniques. A manual search of such image databases is not only exhaustive but is also not efficient therefore various approaches have been presented for the improvement of images retrieval. Accurate retrieval of images from a lot of digital images is challenging, therefore, CBIR is considered as an intensive research area [1-3]. Previously used text-based query methods are not as efficient and effective as feature-based methods. The various primitive features such as color, shape, structure, texture, etc can be used to extract the similarities between the images already stored in database and a query by user [4-8].

These features are called low-level features which are utilized in the search for feature extraction images to match to the large image database [9-10]. There are various CBIR systems that use more than one feature. Color is used in combination with both texture and shape for improved results [11-12].

1. Applications of CBIR:

CBIR is being used in various fields like biomedicine [13-14], medicine [15], military [16], and commerce [17], Art [18,19], Art Galleries [20-21] and Entertainment like content-basedmultimedia retrieval. For Law enforcement [22], CBIR is used for face-detection [23-24] copy-detection [25] while for the control of cyber-crime, CBIR is used in Image-based CAPTCHA [26-27].In the field of bioinformatics, it is used for Automatic Annotation [28], molecular analysis [29], medical diagnosis [30-31] and face recognition [32-54]. The search engines also use CBIR for web-search for images [55]. CBIR is widely being used in biometrics systems. In recent years use of CBIR systems in various fields has been increased.

In this survey paper, a comprehensive overview of the CBIR is presented. In Section 2, CBIR Systems are discussed. Various problem domains of CBIR system are also mentioned along with the classification of CBIR systems. Section 3 gives classification is CBIR systems. In Section 4, few color based techniques used in CBIR systems are discussed. Techniques using the shape featurein CBIR systems are mentioned in Section 5. The summary of various texture based methods over the few years is shown in Section 6.

II. CBIR SYSTEM:

In any CBIR system, there are mainly three phases i.e. feature extraction from query image, feature selection and then the similarity matching. The multi-dimensional feature vectors are created by the CBIR system and these feature vectors are matched with those of database images. The similarity measure or distance measure is done with the help of some algorithm on which score is calculated. The threshold value is pre-defined by the system

Volume: 10 Issue: 01 Pages: 3741-3757 (2018) ISSN: 0975-0290

developer. Those images which have more score than the threshold value are extracted and shown as retrieved results. The Relevance feedback method is adopted so that whether the user is satisfied or not satisfied by the retrieved images then the CBIR system is improved to search keeping in view the selected images by the user.
In Figure 1, a flowchart of CBIR system is shown:

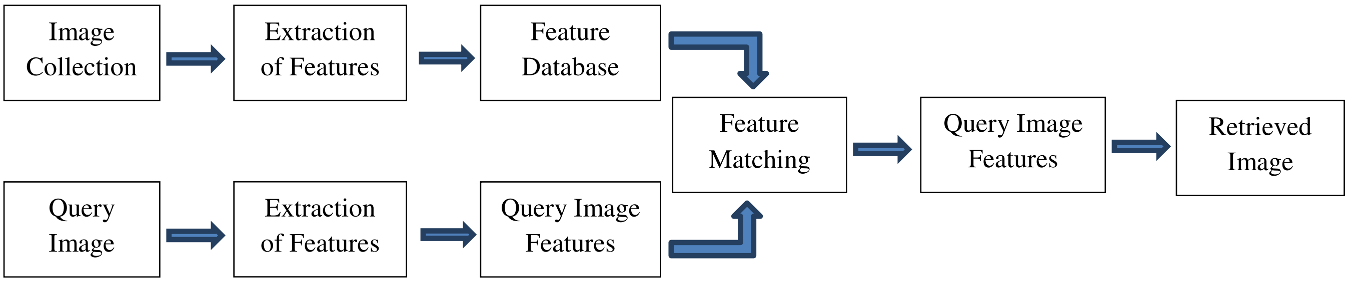

Figure 1: Flow-diagram for CBIR System [69]

2.1. Image Content Descriptor:
An image content Descriptor can be local or global. It can be specific as well as general. Global uses features of thewhole image and local divides image into parts first. A simple method of partition is to use a division i-e cut image into regions having equal shape and size. They may not be meaningful and significant regions but it is a process to represent global features of any image. Partition the image into similar and homogeneous areas is an improved method with the use of some standard such as the Region Segmentation algorithms. Another complex method is to obtain semantically meaningful objects by Object Segmentation. The image content is further classified into two broad categories as visual content and semantic content.

2.1.1. Visual Content:
The visual content is further classified into two main classes:

2.1.1.1. General Visual Content:
When the features or content of the query image are visible and are generally perceived then they fall into this category. Included common visual contents are the features like shape, texture, color, structure, spatial relationship etc.

2.1.1.2. Domain Specific Visual Content:
When the query is based on such content that requires some domain knowledge then those query image content are domain specific visual content like Human Face Detection needs some prior information about the human facial characteristics. These characteristics are not general; these are specific i-e only related to human facial features.

2.1.2. Semantic Content:
The semantic contentsare either described by textual explanation or by using the complex interpretationmeans which are based on some visual-content.

2.2. Image Retrieval Gaps:
The differences between images stored in database and the query image in retrieval are called gaps. The degree of difference will be how far the two images are i-e the gap between the two images. The gaps are divided into two categories: semantic and sensory.

2.2.1. Semantic Gaps:
The mismatching of information of visual query data and the stored image information in the database is obtained. This selected gape to match the image on the similarities basis is called semantic gap. User entered some queries for which optical likeness does not match completely with human perception. By which a semantic gap between CBIR system and the user is obtained [56]. Semantic retrieval has some limitations. A difficulty present in it is that most of the images have more than one semantic interpretation. Because images used for training have usually short description in form of a caption, therefore, some features might never be recognized. This helps to decrease the amount of images instances used for training and weakens the system's capability to be trained for the concepts that are rare and which have a high variable visual appearance. Semantic retrieval system has a limited vocabulary so it mostly generalizes everything other than the semantic space i.e. for which is not trained [57].

2.2.2. Sensory Gaps:
These are the gaps between the real object and the information in form of computational description obtained from capturing that object in an image form. It is the short-coming of the image capturing device.

2.3. Problem Domains:
Retrieving images from a varied and huge collection is difficult. Searching images based on the spatial relationship of portions of a query image is a not an easy research problem in CBIR. As segmentation of regions or objects of an image is not feasible, except in few applications. Another common problem in CBIR is a selection of Features.
The divergence between user's query and the result displayed by retrieval system images is called Semantic gap. These semantic gaps are caused due to the low-level similarity between database images and high-level user-query image this result in an error from search algorithms.

Volume: 10 Issue: 01 Pages: 3741-3757 (2018) ISSN: 0975-0290

RF (Relevance Feedback) is the solution for thesame problem in which the user has the authority to accept or reject the result and requests for better similarity in output images.

2.4. CBIR Methods:

There are different methods used in CBIR. Figure 2 represents the most commonly used methods by the CBIR systems for the image retrieval.
The Features extraction is mostly the initial step in any CBIR system. Each feature selected is placed in a vector named Feature Vector. For Feature Extraction some of the techniques used are the Symbol spotting (graphical shape extraction), [58] background removal approach [59] key-points technique [60]. Some other techniques are the usage of Color, texture, shape, structure, edges as features.

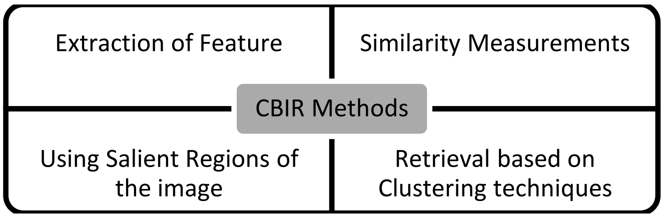

Figure 2: Methods of CBIR Systems [60]

Another method is by the use of Salient region features of the user-defined image. Few examples are the use of the global features of the image [61]. Global features such as the interest points of query image as well as SIFT descriptor are used in CBIR [62-64]. Image Segmentation is also done for better region selection. Common methods are IMALBUM [65], SIMPLIcity, [66] Watershed method and Region growing method (bottom-up).

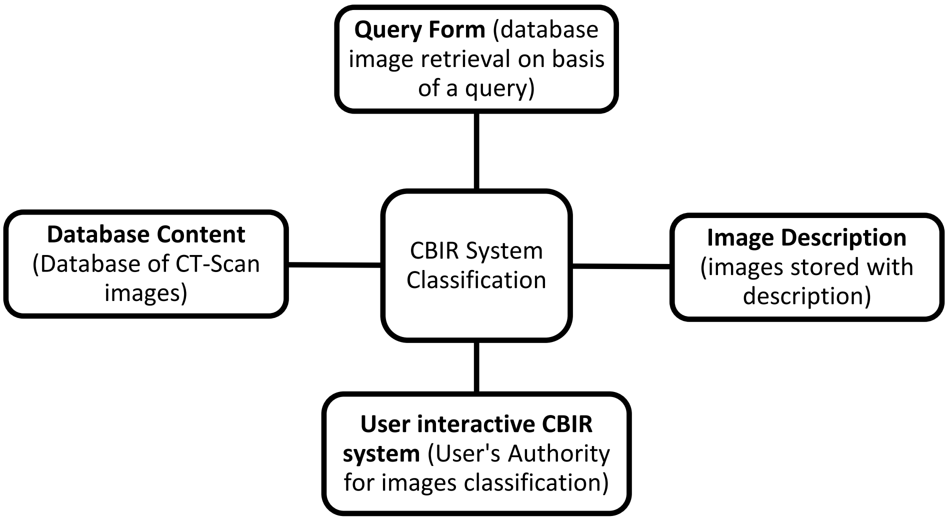

Figure 3: Classifications of CBIR Systems [67]

III. CBIR SYSTEM CLASSIFICATION:

As the CBIR systems are increasing in number there was a need for the classification of these systems. One classification of CBIR systems is shown in Figure 3.Feature such as texture, color, and shape are most frequently used in feature extraction phase of CBIR Systems. The growing need for effective as well as efficient image retrieval has made the selection of an appropriate set of features as the most critical step in the CBIR system formation. In image retrieval research is usually related to the statistical or general methods for the properties of the patches of the image.

IV. COLOR FEATURE:

When viewing an image one of the basic features we observe is color. Color reveals a variety of information. For usage of color as a feature in CBIR, there has been a lot of research done such as the color histogram [68-69], conventional color histogram [70-73], color correlogram, and color moments as shown in Figure 4.

4.1 Color Space:

A point in any 3D color space is represented in form of a pixel. Color spaces like RGB, CMY, and HSV (or HSL, HSB) are widely used. Which color space is the best; there is no consensus for results of images retrieved.

4.1.1 RGB (Red, Green and Blue) Color Space:

In color combination of RGB each pixel has three values which are added together to represent a single pixel value in the color space RGB. Another name for RGB is Additive Primaries as they are added together for giving single pixel value. It is device-dependent and non-uniform.

4.1.2 CMY (Cyan, Magenta and Yellow) Color Space:

CMY consist of three color combinations which are Cyan, Magenta and Yellow. Each pixel has three values which are subtracted to represent a single pixel value in CMY. In CMY color space is formed through absorption of light. It is dependent on the device used and visually non-uniform.

Volume: 10 Issue: 01 Pages: 3741-3757 (2018) ISSN: 0975-0290

4.1.3 HSV (hue, saturation (illumination) and value of brightness) Color Space:

In computer graphics the most used color space is HSV. The Hue is more suitable for retrieval of an object as it is not affected (invariant) to the deviations in light intensity and direction of the camera. A simple formula [74] can convert the RGB coordinates for an image into HSV coordinates.

4.1.4 Opponent Color Space:

It the three axes obtain as R-G, 2B-R-G, R+G+B. The third axis isolates the information about the brightness which is the advantage of opponent color space. As human is sensitive to brightness, therefore, we require a color space which considers the brightness. Opponent Color Space is not invariant to light intensity and shadows hence it is better than the HSV color space.

4.2 Uniformity:

When a color space is selected, uniformity a most important feature is observed [75]. It means that the viewer observes the two color pairs as the same color with same similarity distance. Thus the distance measured among colors should be directly proportional to the perceptual similarity between them.

4.3 Color Descriptor:

CBIR color descriptor can be local or global. Color space selection is important for the color descriptor. As a color space is selected for the representation of the information of color of a pixel of the query image. Quantization of color-space means those colors which are very close to each other and have small distance should be combined together.
There are certain phrases which are followed when color is used as the descriptor. First of all, a color space is designated. Secondly, the quantization of the color space is completed. After quantization color features are extracted. These color features collectively are known as a color descriptor. An appropriate distance function is derived or any particular CBIR System.

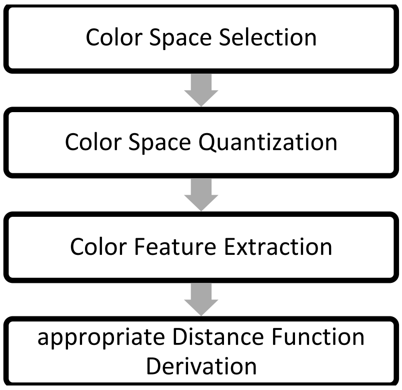

Figure 4: Phases of Color Feature for CBIR [72]

4.4 Color Histogram (CH):

An effective and real representation is a color histogram. A pixel may be represented as 3 components in the histogram of color space. For the color histogram, spatial information about histogram is not considered. This simple approach is used to split the sub-areas for histogram calculation [76-78]. The histogram is a statistical global feature which shows distribution intensity. Color histograms are widely used in CBIR. [79]. Color feature is often used in a combination of texture and structure features [80]. Color Histograms are also useful in recognition of objects. In a large number of images, the matching of the histogram may saturate discrimination. Joint Histogram is the solution [81]. Different color histograms methods have been used for image retrieval. Few of the color histogram methods are described below:

4.4.1 Conventional Color Histogram (CCH)

It shows the frequency of occurrence of each color (no. of pixels having that particular color) within a given image. Every color is connected to its histogram on basis of color similarity. Dissimilarity basis is not taken into account.
To reduce the number of the histograms, Quantization is done. Quantization means to merge two colors histograms which have a similar color. Thus processing time is lessened. Figure 5 shows the CCH steps.

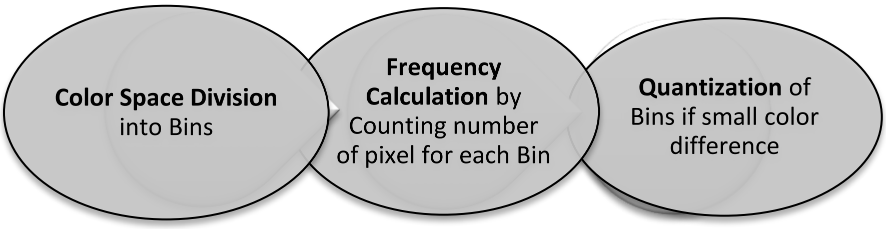

Figure 5: Different Steps of Conventional Color Histogram [73]

Volume: 10 Issue: 01 Pages: 3741-3757 (2018) ISSN: 0975-0290

4.4.2 Invariant Color Histograms (ICH)

Invariant Color Histogram is developed on the basis of color gradients. As the name suggests that it is invariant under any geometry of surface which is locally affine [82].

4.4.3 Fuzzy Color Histogram (FCH):

During merging of different color histograms with the slight difference a problem arises. The color may appear to be similar yet they have a small difference. To overcome this problem FCH concept was introduced. The color space is used for relative greenness-redness and blueness-yellowness) [83].

It also defines the extent of there semblance of the color of a pixel cube for all histograms fuzzy relationship function set given byμ_{ij}. It is stronger to quantization complications as the changes in in the density of light. The drawbacks are that it describes only the FCH features and the global color feature of the image is equally high in dimensionality as CCH. There is an extra computation for fuzzy membership functionμ_{ij}.

4.4.4 Color Difference Histogram (CDH):

This is a recent technique for the image color feature representation [84]. Previously the histogram techniques only counted the number of frequency i-e the occurrence of the pixels. CDH takes the total of perceptual difference in uniform colors between any two points of images under various backgrounds along with the edge orientation and color in the color space L*a*b*.

4.4.4.1 Block Encoding of Color Histogram for CBIR Applications:

Color is a low-level feature yet important feature which is mostly represented as a histogram in different CBIR systems. There are different coding approaches for histogram so that the space used is less and processing is speedy. Recent research on encoding approaches is done by [85]. They have used the Golomb-Rice coding which codes values of the color histogram in floating point by converting them to integers in some pre-processing steps. The histogram is mostly shown in the sparse matrix.

4.5 Color Coherence Vector (CCV):

In CCV [86] spatial information is included in a histogram in a diverse manner. A histogram bin may be classified into two classes i-e Coherent (used for the uniformly-colored large region) or incoherent (not used for the uniformly-colored large region). CCV of an image can be defined as follows in vector form as in equation – (1):

$$< (\alpha_1, \beta_1), (\alpha_2, \beta_2), \ldots\ldots, (\alpha_N, \beta_N) > \quad (1)$$

CCV has additional information as compared to Color Histogram, therefore, it gives better retrieval results.

4.6 Color Correlogram (CC):

It shows the association of colors in terms of distance. CC is presented as indexed in a table by sets of color where the probability of occurrence of any pixel of color j at a distance d from a pixel of I in the given image is represented by the entry for row (i, j) [87].

The space between pixels P1 and P2 is given by in equation – (2):

$$|p1 - p2| \quad (2)$$

The d with a small value is enough to show special correlations as local correlations are more important than global correlation.

CC shows local as well as global spatial information. The disadvantage of CC is that it has high-dimensionality of feature space. For reduction of this dimensionality from ($O(N^2d)$) to ($O(Nd)$) a new feature was introduced. It is known as auto-color correlogram. Auto-correlogram confines the spatial correlation of identical levels only which is shown as given in equation – (3)

$$\alpha^{(d)}(I) = \gamma_{g,g}^{(d)}(I) \quad (3)$$

4.7 Color Moment (CM):

CMare using frequently in CBIR systems which are based on color features. CM of First Order is normally mean, Second Order is Variance and the third order is mainly skewness. These are used in representing color distributions.

4.7.1 Mean - First Order Color Moment:

It is defined by the equation–(4):

$$\mu_i = \frac{1}{N}\sum_{j=1}^{N} f_{ij} \quad (4)$$

4.7.2 Variance - Second Order Color Moment:

Second order color moment is given by the equation - (5) given below:

$$\sigma_i = \left(\frac{1}{N}\sum_{j=1}^{N}(f_{ij} - \mu_i)^2\right)^{\frac{1}{2}} \quad (5)$$

4.7.3 Skewness - Third Order Color Moment:

Color moment third order (skewness) is given in equation (6):

$$s_i = \left(\frac{1}{N}\sum_{j=1}^{N}(f_{ij} - \mu_i)^3\right)^{\frac{1}{3}} \quad (6)$$

The value of the ith-color component of any image pixel j is given by f_{ij} and the total no. of pixels of an image are represented by N. Color Moment is a compact feature as only three moments for each of the three color component are required i-e a total of nine values is needed. Although it is compact yet there is a problem of lower discrimination power.

4.8 Invariant Color Features:

Color changes with the change in illumination [88]. Variability is considered [89]. Invariance to such environmental factor is not regarded as part of most color feature [90-91] Equation for the invariant color feature is as follows given in equation –(7):

$$\left(\frac{R-G}{R+G}, \frac{B-R}{B+R}, \frac{G-B}{G-B}\right) \quad (7)$$

It only depends on the surface and the sensor. For shiny surfaces its equation is given as equation-(8):

$$\frac{|R-G|}{|R-G|+|B-R|+|G-B|} \quad (8)$$

This color-shaped based method considers the color, area and a new feature called perimeter-intercepted lengths of the object-segmentation in a given image [92].The image is segmented into K clusters with the help of K-means algorithm. The object's shape is distinguished by the PILs (perimeter-intercepted lengths). PILs are acquired by the interception of 8 line-segments from the object perimeter. All these 8 lines have different orientations yet pass through the center of the object [93].

Table 1: Comparison of Different Techniques using color as main feature

Sr #	Techniques	Advantages	Limitations
1.	CCH [94]	Simple Computation is easy	Sensitive to noise High-dimensionality problem Cannot handle rotation and translation Global spatial information is not encoded
2.	ICH[95]	Solves the problem of translation and rotation in image	Invariant under any geometry of the surface
3.	FCH [96-97]	Encodes degree of similarity of pixel color by fuzzy-set relationship function Robust to quantization problems Robust to light intensity changes	Describes global color properties of the image only FCH features are equally high in dimensionality as CCH Extra computation for the fuzzy membership function
4.	CCV[98]	CCV spatial information Gives better retrieval results.	Only categorize into two partitions i-e coherent or incoherent
5.	CC[99]	Encodes global as well as local spatial information Works even for coarse color images	High-dimensionality of feature space
6.	CM[100-101]	Compact as only nine values is needed for calculation Less computation	Compact but lower discrimination power
7.	Color-Shape Based Method (CSBM) [102]	Encodes object shapes and colors	More computation Requires an appropriate color threshold Sensitive to noise variation Sensitive to contrast

4.10 Color Image Retrieval Technique based on Color Feature:

From a database of images, for retrieval of similar images, an effective and efficient technique was used by [103]. Some color distributions are used with standard and mean deviation for representation of the global features in any image. The local characteristics of the image were represented by a bitmap of the image. This local characterization increased the accuracy of the image retrieval system.

V. SHAPE FEATURE:

A basic aspect of segmented regions of an image is its shape feature. Its representation is important in the retrieval of similar images [11]. The shape characteristics are extracted and matched with the database image collection, therefore; the shape feature representation is most significant [10].

There are different methods introduced to help in better retrieval by using different shape representation techniques [104]. Earlier the global shape representations were used but with time they move towards local shape representations as local descriptors produce better retrieval results [105-106]. Shape representation using discrete curve evolution for contours simplification removes irrelevant shape features [107].

5.1. Shape Context (Shape Descriptor):

For similarity matching a shape descriptor called shape context was proposed which was useful for varying geometric transformations [108]. Shapes approximation as concave and convex segments was the approach of Dynamic Programming for shape matching. The only problem with it was that there was pre-computation for the Fourier Descriptor and moments in this technique which was slow [109].

5.2. Local Shape Features:

In the local shape feature, all the characteristics related to the geometric details of an image [110]. The local shape is more related to the expressing of result instead of the method [111]. Local shape features may be derived from the texture properties and the color derivatives.

5.3. Scale-Space Theory for Shape Feature:

Scale-Space theory was advised for capturing all the prominent information, [112]. It gives the basis for the

Volume: 10 Issue: 01 Pages: 3741-3757 (2018) ISSN: 0975-0290

detection and recognition of some prominent features and details on any scale.

5.4. Shape Affine-Invariant Descriptor:

Differential geometric invariant and affine-invariant descriptor are also available [113]. Color feature and shape have been combined in invariant method [114-115].

5.5. Object-Shape Feature:

Theoretically, the best approach by segmenting the object for the object-specific information of imagesis within the image [116]. It is not necessary to recognize the exact location of features of the object in an image but it is important to identify the presence of an object with the help of its properties. When segmentation is done as shown in the equation–(9)

$$t_j(x) = s_j \circ f(x) \quad (9)$$

The shape of an object is shown in equation-(10):

$$F_j = \sum_{T_j} h^\circ t_j(x) \quad (10)$$

Where h shows the functional computing shape and $\sum$ show the aggregation operation. This equation is for the accumulative features. Some features have general applicability like moment invariants and the Fourier features of objects [117].

For the image retrieval, there is a requirement for the shape representation that measures the distances of deformations. Some mismatch images are acceptable in certain interactive use of retrieval. So compromise on accuracy may be possible as we need a system to be robust and computationally efficient [118]. There are sophisticated methods like elastic deformation of image portions, multi-resolution representation of shapes and modal matching techniques [119-120].

5.6. Contour Multi-scale Model:

Multi-scale models of contours have been studies for database image representation. There are two approaches to Contour multi-scale model:

a) Multi-Scale Model of Contours as Database Image Representation
b) Multi-resolution Shape Model for Contours.

These two approaches for contours use are shown in Fig 6.

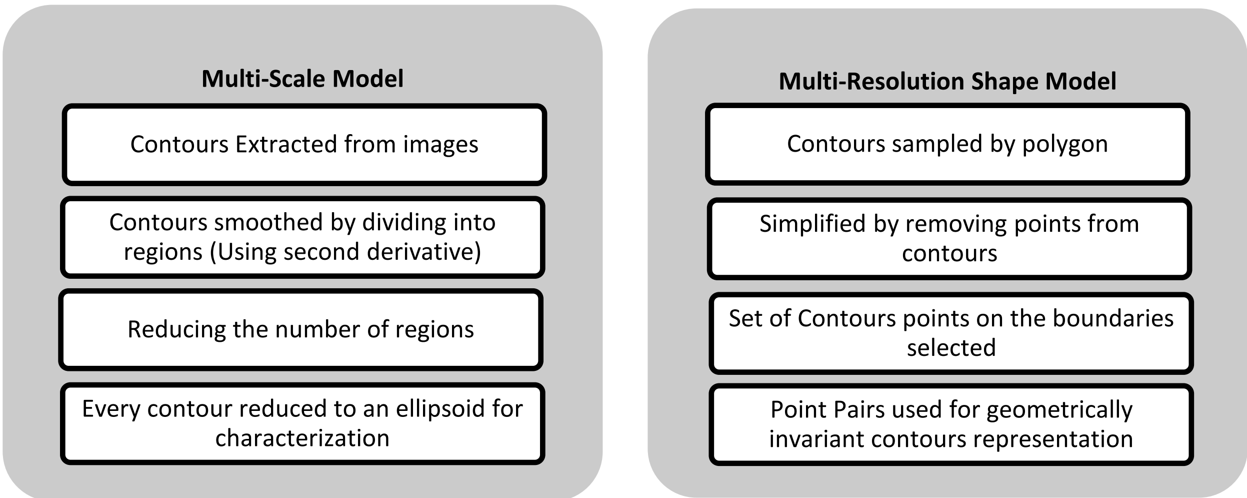

Figure 6: (a) Steps of a Multi-Scale Model of Contours as Database Image Representation (b) Steps of Multi-resolution Shape Model for Contours. [121]

5.7. Contour Representation:

The images have to process for retrieval which comprises a group of operations on the contours. Edge-contours are represented by the B-spline. There are three detection types of symmetries: Skew and parallel symmetries are used for inferring shape from the contour. The third type of symmetry is smooth local symmetries used for planar shape description [121].

VI. TEXTURE FEATURE:

In Image processing as well as in computer graphics and computer vision the texture features are widely used [122] like wavelet transforms, discrete cosine transform [123] and curvelet transform. Many textures are composed of the small textons which are numerous and thus cannot be perceived as separate objects.

6.1 Structural Pattern Feature:

Various texture features are proposed for analyzing the structural pattern information in an image. These texture features include Co-Occurrence of gray-scale values [124], multi-resolution analysis [125]; Local Pattern Spectrum [96] and texture unit spectrum-based [126-127] techniques.

6.2 Gabor-Filter Based Techniques for Texture Feature:

Popular Techniques include Gabor-filter based techniques [128-129] Wavelet Decomposition with energy signatures [130] and Gaussian Markov random field (GMRF) models. The query image is afterward convolved with each Gabor functions obtained after the parameter settings. It has been shown that for the highest texture retrieval results, Gabor Transform for texture feature is used in

Volume: 10 Issue: 01 Pages: 3741-3757 (2018) ISSN: 0975-0290

CBIR [131]. Results of the Gabor Transform function is an over-complete demonstration of the user's query image with a certain redundant ratio of K*S (scales*orientation).

6.3 Modified Gabor Function:

Gabor transform has to be applied from all orientations as it depends on the direction. The angles used have an effect on the results of the image retrieval. Therefore the existing Gabor transform had to be modified. The modified Gabor transform is independent of the angle selection. Its performance is almost equal to the simple Gabor Transform.

The modified Gabor Transform is invariant to the rotation. Because of this invariance for rotation, the modified Gabor Transform showed better results in almost all the images [132].

6.3.1 Contourlet Transform for Texture Features:

These are based on directional multi scale filter bank which deals with the smooth contours of the images. Contourlets allow various directions at every scale which in turns gives a critical sampling. They give directionality as well as wavelets features. Figure 7 expresses the comparisons of Gabor Wavelet Transform Method and Contourlet Transform approach is shown.

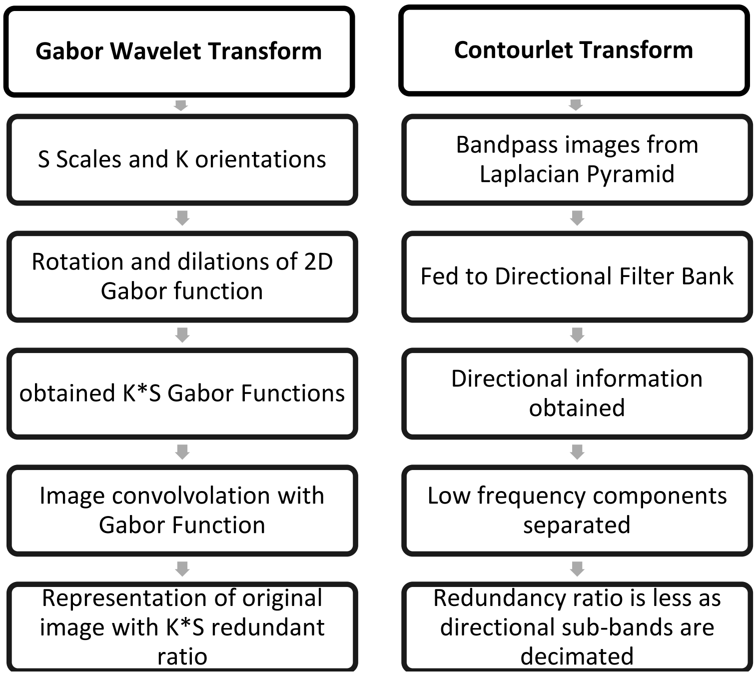

Figure 7: Comparison of Gabor Wavelet Transform Method and Contourlet Transform Method [127]

6.3.2 Gray-level Run Length Technique for Texture Feature:

Gray-level run length is useful when analysis at more than single orientation is to be done for the extraction of structural information. Spectrum-based techniques are also not recent [133]. With time signal-processing has attained progress which results in the efficient power spectrum tools for analysis. Earlier techniques were gray-level run length [134] gray-level co-occurrence matrix [122]. Some models utilize statistical regularities in the texture field while other models take texture as result of a deterministic dynamic system which observes noise.

6.4 Techniques for Transformations of Texture Surfaces:

A collective problem is that for the texture feature extraction the image with texture surfaces has to undergo numerous scaling and re-orientation steps but it is a computationally difficult task. Previously Pyramid Structured Wavelets [135] tree-structured wavelets [136]; multi-resolution simultaneous autoregressive models were the multi-resolution technique but the Gabor filters have shown better performance [137].

6.4.1 Techniques for Illumination Effect on Texture Surfaces:

The recent algorithms proposed for the texture analysis consider the non-ideal conditions like illumination intensity change due to the source itself or the capturing device, texture viewing angle change and spectral attributes of light [138]. In the real-world scenario, there are certain environmental factors like changes of light directed from source [139]. Changes in the spectral attributes of light also have an effect on the texture of the image surface affecting the inter-class distances as well as the intra-class of the textures [140].

Volume: 10 Issue: 01 Pages: 3741-3757 (2018) ISSN: 0975-0290

6.4.2 Algorithms for Changes in Affine Transformation and Light Attribute:

Affine Transformations like rotation and scaling of images affect the texture surfaces [141-142], the non-affine transformations like 3D orientation changes also affect texture characteristics [143]. In the real-world, the 3D nature of the textured surface may significantly change the observed texture data by light direction change [144]. Some of the recent texture analysis algorithms are LPB uniform for the changes in spectral attributes of light and LPBrotational invariance for the changes in affine transformations [145].

The common texture analysis algorithms are Gray-Level Co-occurrence matrix (GLCM), Gabor filters, LBP with Rotation Invariance, Local Binary Patterns (LBP), LBP with Contrast Measures, LM 3-D Textons [146], MR8-Textons, Multi-scale Opponent Color Representation and Multi-resolution Histogram [147]. In graphics field, there are researches in the texture synthesis field where on the adjacent orientation of pairs of wavelet coefficients in the images, the statistical descriptor is based. To extract the texture features the coefficients of a transform are used on the original pixel values of an image by statistical computations [148].

6.5 Texture Descriptor:

Texture feature was used for image retrieval even in 1996[149]. Texture Descriptors encoded general visual attributes into a numerical form which can be easily used for the computational tasks [150]. Some advance textured descriptors are affine transform and photometric transformation invariant features [151]. Improved affine-invariant transform designed for the texture recognition were used in point detection [152].

6.5.1 Wavelet Transform:

Wavelet feature performs well when the texture images were rotated [153]. Wavelets have been used for their compression efficiency and their locality. The various wavelet transforms generates series of rotation and dilations. Lowest levels of wavelet transforms are used for the texture representation [154-156]. A comparative study of the early works done on texture classification from transform-based characteristics is done [157].

6.5.2 Wavelet Packet Signature Methodology:

A generalization of supported wavelets is Wavelet packets [158]. The use of wavelet packet was initiated by Coifman et al.[159].The wavelet packets are ortho normal [160] and are localized in both frequency and time and thus can be used an alternate for the Fourier (frequency based) analysis. The methodology for the texture classification by the help of wavelet packet representation was introduced [154]. The minimum-distance classifier used was Euclidean Distance. Texture Classification by Wavelet Packets Signature Methodology is shown in Figure 8.

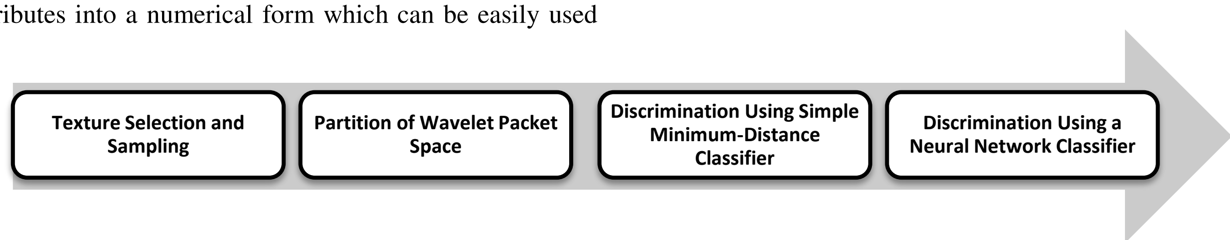

Figure 8: Texture Classification by Wavelet Packets Signature Methodology [151]

6.5.3 Multi-Resolution Wavelet Packet Method:

Texture signatures that were based on the multi-resolution wavelet packet method showed potential for accurate classification and discrimination. For texture segmentation, the methods of scale-space analysis which was done using this method gave efficient representation [161].

6.5.4 Wavelet Packets and Fuzzy Spatial Relations:

In CBIR system the relevant database images with respect to the user's defined image are recovered using the features like texture, color, and shape [162]. But there was a need for more sophisticated image retrieval system for this a method based on the wavelet packets was introduced. The Fuzzy similarity measure was introduced in FIRM [163] in which fuzzy features were used. Wavelet transform provides structure for analysis and at different scales properties of images [164].

6.5.5 Local Spatial Frequency Properties for Texture Features:

Local spatial frequency properties can be utilized to obtain attributes of texture. These attributes can be shared in the wavelet area by wavelet filter for convolution in the spatial area. For the extraction of colored texture mixing of wavelet features was done [165]. For multi-resolution Feature Extraction, the arbitrary tree structure was used, analysis of multi-resolution considers the spatial similarities across sub-bands [166].

6.5.6 Application of Texture Features:

Texture features have been used for images of documents, [167] segmentation-based recognition, [168] and satellite images. [169] Texture features are used in various CBIR systems along with color, shape, geometrical structure and sift features.

6.6 Color Co-Occurrence Matrix for Texture Feature Extraction:

A unique method is introduced which is used to color co-occurrence for extraction of texture feature and for measuring similarity into two color images [170]. The feature obtained gives information about the texture correlation [171] and color information. This technique gave better result in terms of retrieval accuracy (recall and precision) as compare to the GLCM and histogram technique.

Classification of various methods used for feature extraction mostly comprises of two main categories statistical based feature extraction and structural based feature extraction. Statistical feature extraction methods are a morphological operator, adjacency graph, and co-occurrence matrices while statistical feature extraction methods are world decomposition and Markov random field. The categories are shown by the help of following diagram [172-173]. Categories of Feature Extraction Methods are given in Figure 9.

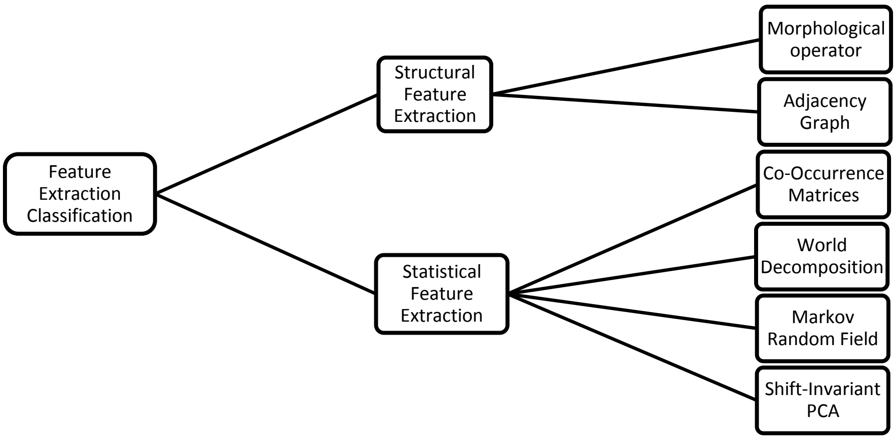

Figure 9: Categories of Feature Extraction Methods [172-173]

VII. CONCLUSION:

Large databases of images have to be searched to retrieve query related images with the help of CBIR System. A manual search of such image databases is inefficient and exhaustive. Accurate retrieval of images from numerous digital images is challenging, therefore, CBIR Systems is an intensive research area. Semantic Gap is a deviation from the information that is acquired from visual query data and the already stored information in the database on the similarities basis. For better retrieval of images from databases, certain features are used. Feature such as shape, color and texture are most generally used in feature extraction phase. Growing need for effective image retrieval has made the feature selection phase the most critical step. This survey paper consists of the brief introduction of features of CBIR system. Color feature is observed at first. Different color spaces are defined in research work related to the use of the color feature in CBIR system. A comparison of different techniques using color as the main feature is presented in this survey. The shape is the basic characteristic of segmented regions of an image. The features of shape are extracted and matched with features already saved in database for images. Global shape representations, as well as local shape representations, are used forshape descriptors produce better retrieval results. Local shape descriptors are related to the geometric details of an image. Local shape features may be derived from the texture properties and the color derivatives. Texture features are used in various CBIR systems along with color, shape, geometrical structure and sift features. Some advance textured descriptors are affine transform and photometric transformation invariant features. Improved affine-invariant transform designed for the texture recognition were used in point detection. A common problem with texture feature extraction is that the image with texture surfaces has to undergo numerous scaling and re-orientation steps which are computationally difficult tasks. Previously Pyramid Structured Wavelets, tree-structured wavelets, multi-resolution simultaneous autoregressive models were the multi-resolution technique but the Gabor filters have shown better performance. Some recent work in the field of CBIR features is also discussed in the survey paper.

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AUTHORS' PROFILES

Anum Masood, Lecturer, Department of Computer Science, CIIT, Wah Campus, received her Master of Computer Science and MS (CS) degree from COMSATS Institute of Information Technology, WahCantt. She is now serving as Lecturer, Department of Computer Science, CIIT, Wah Campus. Her areas of interest are Image Processing, Computer vision, and Medical Imaging.

Muhammad Alyas Shahid received his Master of Computer Science degree in 2002. He received his MS(CS) in 2017 from COMSATS Institute of Information Technology, WahCantt with specialization in Image Processing. He is into teaching field from 1998 till date. Currently he is serving as a Lecturer of Computer Science in POF Institute of Technology, WahCantt. His research interests are Image Processing, Multimedia Processing, and Computer Networks & Security.

Muhammad Sharif, PhD, Associate Professor COMSATS Institute of Information Technology, WahCantt received his MSc in Computer Science from Quaid-e-Azam University, Islamabad. He received his MS(CS) and PhD(CS) from COMSATS Islamabad with specialization in Image Processing. He is into teaching field from 1995 till date. His research interests are Image Processing, Computer Networks & Security, Parallel and Distributed Computing (Cluster Computing) and Algorithms Design and Analysis.