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Review on Content Based Image Retrieval: From Its Origin to the New Age

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Abstract: *Content Based Image Retrieval (CBIR) is a process in which for a given query image, similar images will be retrieved from a large image database based on their content similarity. The content of image refer to its features or attributes or parameters which are mathematically determined from a digital image. In this approach the images retrieved may not exactly match with the visually similar or semantically similar images. Semantic similarity refers how far the user expectation meets the retrieval. Content Based Image Retrieval gained its importance from early 1980's and still got lot of scope for the research community to find more sophisticated methods to improve the retrieval. Content Based Image Retrieval got its significance in domain specific applications such as biomedical and satellite imaging etc. In this paper we presented an exhaustive literature review of CBIR from its inception to till date, with all the new approaches that has included in this process. We present our review on benchmark image databases, color spaces which are used for implementation of CBIR process, image content as color, texture and shape attributes, and feature extraction techniques, similarity measures, feature set formation and reduction techniques, image indexing applied in the process of retrieval along with various classifiers with their effect in retrieval process, effect of relevance feedback and its importance in retrieval. This survey paper can be viewed as an exhaustive literature review of CBIR from its origin to the new age.*

1. Introduction

Content Based Image Retrieval gain its importance over last few decades in multimedia and other domain specific applications like medical and remote sensing. Many people got interest in CBIR because of its wide variety of applications and huge research has done in terms of visual features, feature extraction techniques, similarity measures for basic image retrieval process and the additional approaches as relevance feedback, region based image retrieval by incorporating segmentation, indexing and classification methods using clustering Fuzzy and Neural networks, semantic CBIR with new visual descriptors to improve the performance of existing CBIR systems. In this paper we have done an exhaustive survey on the research done in CBIR from the basic level to the new age. Challenges evaluations and techniques towards efficient CBIR presented in [5], [38], [40], [83], [198]. [68], [89], [90], [107], [120], [124], [164], [180], [189]–[191], [209] surveyed on low level visual features to high level semantic features that are used in CBIR. [93], [100], [108], [186], [222] detailed on shape features [68], [107], [112], [142] explored effect of distance measures for CBIR. Image indexing and feature reduction clustering and classification methods discussed in [81], [122], [176]. Effect of relevance feedback in CBIR explored in [7], [43], [147], [154]. Modifying the queries and their effect on retrieval discussed in [49], [56]. Inclusion of Neural networks, Fuzzy usage and Support vector machines and other feature reduction techniques explored in [11], [35], [43], [86], [154] Ontology refers to domain knowledge and [69], [213], [214]. [46], [107], [121], [125], [141], [142], [167], [169], [195], [196] presented various techniques to achieve semantically equivalent image retrieval.

2. Image Databases

In this section we presented various publicly available image databases to use for Content Based Image Retrieval Algorithms. The data bases include color, gray scale, texture, shape, segmented and medical images including various natural scenes, faces, animals, buildings, persons, retinal and many more, all of these images will motivate us to work in different dimensions of CBIR to improve the retrieval process.

2.1. COREL Database

This database is created by James J. Wang and Jai li at University of Pennsylvania State University, Stanford [105]consisting of 10,000 test images and a subset of 1000 images in different sizes in .jpg format. In [196] authors used statistical modelling approach and each image represented by a concept and images of any concept regarded as instances of a stochastic process and 2-D Hidden Markov Models were used.

2.2. WANG Database

This database consists of 1000 multiclass images of .jpg format in 10 groups each of 100 images. developed by James G.Wang, Jaili, Giowiderhold at University of Pennsylvania State University, Stanford. in the base paper [Wang] wavelet based approach is used for feature extraction. Integration region matching is done based on segmentation. Semantically adaptive techniques are used for relevance estimation.

2.3. MIRFLICKR

This database is introduced by Medialab Image Retrieval Committee in 2008 (25,000) and in 2010 (1Million). Original images are available through bit torrent. This database is developed by Mark Huiskes, Bart Thommee, Michael Lew at LIACS Medialab, Lciden university, Netherlands. all the images are in .jpg format in 64 x 64 thumbnail version. In papers [76] [77] authors used images in CLEF 2009 - 2012 for visual concept detection and annotation task. All images made available under creative common attributes licence. MPEG7 edge histogram, Homogeneous texture descriptors and ISIS group color descriptors are used as CBIR descriptors.

2.4. UW Database

This database is created by Thomas Deselaers et al in dept. of CSE at University of Washington consisting 1109 images of different sizes in .jpg format. These images were vacation pictures of various locations which are divided into 18 categories and semi annotated with key words. All these images were annotated and the complete annotation has 6,383 words with a vocabulary of 352 unique words. The number of keywords per image varies from 1 to 22. This database can be freely downloaded from the web link.(http://wwwi6.informatik.rwth-aachen.de/Deselaers/uwdb/ index.html)

2.5. ZuBuD Database

This database is created by Prof. Luc Van Gool and Prof. Gbor Szekely, in Dept. of. IT and EE Computer Vision Laboratory, ETH, Swiss Federal Institute of technology, Zurich, Switzerland. This database consists of 1005 training images of 201 Zurich Buildings taken in 5 different angles. and 115 images were used for testing purposes. all these images are of different sizes in .jpg and .png format. The base paper [161] give detailed information of this database. and also to find good combination of color and shape descriptors so that for a given query same buildings must be reproduced irrespective of its size and shape.

2.6. ETHZ Shape Classes Database

This database consists of 255 images created by V.Ferrari, F.Zuri, L. Van Gool and T. Tutelaers at ETH Zurich Switzerland, all the images are of different sizes and in .png format. the database is created for testing object class detection algorithms. the use of this database is given in the base papers and [47], [48] and [140]. Five diversified shape based classes apples, bottles, Giraffes, mugs and swans are available in this database. 1) ETHZ Extended Shape Classes: This is a 455 image database created by merging ETHZ shape classes with Konrad. developed by K.Schindler and D.Suter. All images are of different sizes in .png format. The base paper [159] explore more details of this database.

2.7. UCID.V2 Database

This is an Un Compressed Image database of 1300 images in .tif format, created by G.Schaefer and M.Stich at Nottinghom Trent University, U.K. According to [158] and [71] this database is used for evaluation of various image retrieval techniques that operate directly in compressed form and to compare the effect of compression on retrieval process. Manual relevant assessments were created. most of the images are relevant but their precision and recall will vary.

2.8. Oliva Database

This database consists of 2000 images created by Aude Oliva, Ph.D, at MIT, USA. the database consists of natural and urban scene color images in .jpg format, according to [130] the data set consists of eight semantically organized classes.

2.9. Caltech Database

It is a face database of 10,524 images of 7,092 faces developed by Micheal Fink and Rob Fergus at California Institute of Technology, USA. All images in this database are of fixed size 304 x 312 and in .tif format. Face detection algorithm based on the positions of eyes, nose and mouth in [9] used this database.

2.10. NUSWIDE Dataset

This is a real world web image database consisting 2,69,648 images with 5000 tags from Flicker, developed by Dr. Yue Gao, Mr. Xiongyu Chen, Dr. Jinhul Tang at National University of Singapore. All the images are of different sizes in .jpg format. Complete details given in [32]. Six types of features extracted from images: 64-dimensional color histogram, 144-dimensional color correlogram, 73-dimensional edge direction histogram, 128-dimensional wavelet features, 225dimensional block wise color moments and 500-dimensional bag of words using SIFT descriptors. K-Nearest Neighbor (KNN) algorithm implemented. Ground truth for 81 concepts used in evaluation.

2.11. INRIA Database

This is a database of 1800 images of persons developed by Navneet Dalal and 1441 images of holidays by Herve Jegou, at Agence Nationalle de la Recherche, INRIA, France. All these images are of 64 x 128 in size and are of binary format. [32] proposed techniques to detect upright people in image and video from the images with persons an different background. In [84] consists natural, man-made, water and fire images, to test robustness of various attacks, images tested with 128dimensional SIFT descriptors.

2.12. BSDS 500 Database

This is a Berkeley Segmentation bench mark database of 500 segmented images developed by Pablo Arbleaz, at Berkeley University of California, Computer Vision Group. the images are in different sizes and are in .seg format This data set is provided for image segmentation and boundary detection applications. In [10] Contour detection, Hierarchical Image Segmentation implemented and produced interactive segmentation tool in matlab.

2.13. Brodatz Database

This is a multiband texture database (MBT) of 154 color images and Colored Brodatz Texture database (CBT) of 112 gray scale images developed by Safia. A. He.D at Uniersite de Share brooke, Canada. in [1], [155] it is given that images from MBT has two important characteristics, Chromatic content and texture content represented by intraband and interband spatial variation. In CBT, color is removed and only mono band texture is only the source.

2.14. Outex Database

This is an Oulu texture image database with 27,054 images with 320 textures including both micro and macro textures developed at Centre for Machine Vision Research, Dept. of Computer Science, University Oulu, Finland. All the images areof24-bitRGB, 8-bitgrayscalewith1712x1368pixelsize. this is a frame work for an empherical evaluation of texture classification and segmentation algorithm. mainly emphasized on Texture classification, Supervised and unsupervised texture segmentation.

2.15. VISTEX Database

Vision Texture VISTEX is texture database created in 1995 by MIT to provide high quality texture images for computer vision applications. The database consists of 165 compressed and 240 uncompressed images and has four main components: Reference textures, Texture scenes, video textures and video orbits. This database is available from Media Lab. the images are in 786 x 512 size. all images are annotated with six key words. This database can be download from link

2.16. IRMA Database

IRMA Image Retrieval in Medical Applications database consists of fully annotated radiographer arbitrarily taken from Department of Diagnostic Radiology Aachen University of Technology RWTH Aachen, Germany. All IRMA images fit in 512 x 512 pixel size. This database is created every year and is used in CLEFMED medical image retrieval task challenges. IRMA project is funded by the German Research Foundation and was supported via the START research program by the Medical School, Aachen University of Technology. IRMA uses morphological image processing technology Morphoscope for determining the seed points of the hierarchical clustering. IRMA uses WilmaScope Java Engine. These image databases can be downloaded from the link given in https: //ganymed.imib.rwth − aachen.de/irma/datasetsen.phpwithspecialpermissions.

2.17. CXRO Database

This is also an optic related database available at link given in https: //ganymed.imib.rwth − aachen.de/irma/datasetsen.php

2.18. DRIVE Database

DRIVE: Digital Retinal Images for Vessel Extraction database consists of 400 retinal images developed by Bram Van and Ginneken at Image Sciences Institutes Netherlands. All images are in 768 x 584 size in .jpg format. the database is established to enable comparative studies on segmentation of blood vessels in retinal images obtained from diabetic retinopathy screening programme. [174].

3. Features of a Digital Image

A digital image can be characterized by its attributes or features which are its mathematical representations. The features categorized as color features, texture features, shape features and canonical features. Various transformation coefficients were also considered as image features. Features for image retrieval described in detail in [42] with experimental comparison and concluded same set of features will not work good for different datasets. In other sense image features categorized as low level visual features, scale, rotation and translational invariant features and high level semantic features. [17] proposed Speed Up Robust Features SURF is an example. In this section we presented image features: color, texture and shape and the so far research done on these features.

3.1. Color Features

Color features are the most powerful features to represent image content and has given at most importance in image processing and retrieval. Color features of an image are the intensity values of a pixel obtained in any color plane representation of a image. So we start with various color spaces available in literature to use in image retrieval and other applications. We present various ways to denote the color content of an image such as color histograms, color correlograms, color coherence matrix, dominant color descriptors and color sets.

3.1.1. Color Spaces

Color spaces are usually non-luminance such as RGB, HSV, HSI and XYZ or luminance-chrominance color spaces of YCbCr LUV, YUV, YIQ, YCgCb and Lab*planes. HSV or CIE Lab and LUV spaces are used to represent color and they are human perception based [123]. CIE (International Commission on Illumination) is a color standard system established in 1931 and other CIE standard color spaces are xyY, U*V*W* and Lu*v*. Red Green Blue (RGB) is a primary color plane representation. It is the simplest representation a color image and highly sensitive to pixel intensity variations [173] these three primary colors represented in Cartesian coordinates. All three intensities need to be modified to change a single color value, due to this RGB plane is not effective in real world image processing. Digital RGB values usually ranges from [0,255] with 8-bit quantization. Cyan Magenta Yellow (CMY) are secondary colors which are exact complements of RGB. In luminance chrominance color spaces viewers first notice a color’s hue and then other characteristics i.e lightness, brightness, brilliance, strength, saturation, vividness, purity, etc., many of which are interrelated [88]. Hue Saturation Value (HSV) plane is more robust way of image representation and most of the time color features calculated in this color space [8], [103], [110], [179], [215]. Hue denote dominant spectral component i.e color in purest form and is a circular quantity. More saturated color has lesser white component and value (V) represent the brightness of color. All these three quantities specified in cylindrical coordinate systems. Dark colors are insensitive to saturation but hue changes. YUV color space is used by popular video standards PAL, NTSC and SECAM. In this Y represent luminance component and UV represent color information [173]. The advantage with this is black and white receivers can reproduce a gray image based on Y component by neglecting U and V. For digital RGB values[0,255] Y ranges from [0,255], U from [0 , 112] and V from [0 , 157]. YIQ color space is a slightly modified version of YUV in which I represents in-phase and Q represent Quadrature phase components. with YUV space content based image retrieval efficiency improved [177]. YCbCr is scaled version of YUV space and in this plane image is represented by its luminance and chrominance values where Y is the luminance component ranging from [16,235], Cb and Cr are the chrominance components range from [16,240]. YCbCr formats prescribed in different sampling rates. [173]. This color space is mostly used for skin color classifications [139]. Right choice of a color space for a particular problem described in [4]. Perceptually uniform color spaces for texture analysis presented in[133]. A Bayesian approach for skin color classifications and face detections in YCbCr space analyzed in [23]. Color based image retrieval based on Block Truncation Coding (BTC) in YCbCr color space presented in [95]. CBIR with multilevel BTC in nine sundry color spaces RGB, HSI, HSV, rgb, XYZ, YUV, YIQ, YCgCb, YCbCr and Kekre's LUV presented in [94] and proven that luminance based color spaces performed well over non luminance color spaces. In [114] Hue-Min-Max-Difference HMMD color space was proposed where H represents Hue, Max and Min are the maximum and minimum values among RGB and D is the difference between the Max and Min values, it is more effective than HSV and HSI color spaces.

3.1.2. Color Histogram

Color histogram is a simple, powerful and widely used color feature. It gives the joint probabilistic distribution of intensity of three color channels in an image. Color histograms can be computed in all forms of color spaces. A color histogram is obtained by discritizing the image colors and counting the number of times each discrete color occurs in the image. Histograms are invariant to translation and rotation. content based image retrieval techniques based on color histograms presented in [41], [49], [52], [85], [127], [136], [175], [181], [212]. First color indexing process by using color histograms for stable object representations and Histogram Intersection for similarity matching and Histogram back projection for solving location problems [181]. In histogram back projection model a ratio histogram is computed from a query and image histograms. [175] proposed a color indexing schemes using Cumulative Color Histograms (CCH)with L1, L2 distance metrics for similarity measurement. pros and cons of color interest points along with their optimal use given in [52] where the point characterization obtained from combinations of the Hilbert's differential invariants. To reduce histogram dimensionality uniform scalar quantization is popularly used in which spatial information get lost. To overcome this drawback Gaussian Mixture Vector Quantization (GMVQ) used to extract color histograms [85]. In this approach spatial information preserved by clustering groups of pixels. Even with a penalized log-likelihood (LL) distortion, this method shown better retrieval performance for color images than the conventional methods of uniform quantization and VQ with squared error distortion. In [212] color histograms were computed in HSV color space by splitting the image into annular isometric regions and its shown improvement in retrieval efficiency compared with simple histograms. Color histograms have advantages like robust, fast, less memory requirements , straight forward implementation and best suited for global color description [171], the drawbacks include high dimensional feature vectors, loss of spatial information about color spread, immune to lightening variations and comparison of histograms is computationally extensive.

3.1.3. Color Coherence Vector

As spatial information is missing in color histograms a split histogram called Color Coherence Vector (CCH) was proposed in [134] where each histogram bin is partitioned according to spatial coherence based on local properties. A color coherence vector (CCV) stores the number of coherent versus incoherent pixels with each color. By separating coherent pixels from incoherent pixels, CCVs provide finer distinctions over color histograms. Histogram refinement easily distinguish images whose histograms are almost equal. In [135] histogram based comparison is described where each pixel in a given color bucket classified as coherent or incoherent based on whether or not it is part of a large similarly-colored region. Performance of Spatial color histograms, annular color histograms, angular color histograms and hybrid color histograms were analyzed in [143] and shown improvement over CCVs.

3.1.4. Dominant Color Descriptor DCD

Color descriptors originating from histogram analysis have played a central role in the development of visual descriptors in MPEG-7 [114]. Dominant Color Descriptors (DCD)s indicate the salient distribution of the color in the region of interest. It extract few dominant colors from image. DCD contain two main components, representative colors and the percentage of each color [199]. Dominant color descriptors used as color features in [114], [137] generate representative colors and their percentages in an image. A region based dominant color descriptor indexed in3D space along with their percentage coverage with in the regions shown good performance over traditional multidimensional histograms in [41]. [175] proposed color moments or color distribution features by choosing first three moments of the distribution in each color channel. The first moment is average and variance is the second central moment and the third one is the skewness. With color moments only dominant features are used with which retrieval process runs faster and better results were obtained. Correlation between these three color moments to produce a 3-D distribution suggested as a future work. In DCD the representative colors are computed from each image instead of being fixed in the color space, accurate features in reduced size were obtained. To compute this descriptor the colors present in a given region/ image got clustered [41]. Other works including DCDs in CBIR were [119], [144], [145], [162], [203], [204]. CBIR using a weighted DCD and a new similarity measure was proposed in [183] in which more weight age is given to object colors rather back ground colors.

3.1.5. Color Correlograms

A new image feature called color correlogram for image indexing proposed in [73], [75]. A color correlogram expresses how the spatial correlation of pairs of colors changes with distance and captures both color and spatial distribution, gives spatial information of pixels in an image. Correlogram is more robust to zooming, rotation and scaling and considered as a generic tool for spatial color indexing and hence more efficient than histograms. CBIR achieved with color correlogram by including relevance feedback and two supervised learning techniques of learning the query and learning the metric in [72]. Color Auto Correlogram extracts spatial distribution between exactly similar colors, with which computational complexity gets reduced Semantic CBIR using correlograms in HSV space with more sensitive changes to hue and less sensitive to saturation and value described in [128].

3.1.6. Color Difference Histogram

Color Difference Histogram CDH counts the uniform color differences, between two pixels under different back ground with respect to their color and edge orientations in La*b* color space. CBIR using color difference histograms presented in [217]. It is also observed that CDH is much more efficient than histograms, correlograms and color descriptors.

3.1.7. Color Based Clustering

Color Based Clustering (CBC) is said to be one of the effective approach among all color based features. [211] proposed a new approach for text identification from an image with color based clustering. color image segmentation using color based clustering described in [210]. Color clustering done in Lab space by choosing circularly chosen cylindrical decision elements for making clusters citecelenk1990color. Color text extraction with metric based clustering presented in [113]. Brain tumour detection using color based k-means clustering segmentation discussed in [205]. 8) Color Sets: Color sets developed by Smith and Chang are an alternative to color histograms to represent the color content of images and regions [171]. They used for quick search in large image data sets. RGB image first transformed into HSV space and then quantized. A new method of color extraction using back projection of binary color sets to select more occurent colors in a given region proposed in [171] with which regions and their color content were extracted automatically. As the color sets are binary vectors, they can be indexed efficiently. A color set is denoted as the group of pixels in an image with same color and these visible colors divided into eleven JNS colors [24]. The colors in a region are represented as a binary color set based on the histogram presented in [74]. [126] proposed a color constancy algorithm using a color chart, it can make the color recognition even with variation in lighting. In [208] a novel image retrieval using multi granularity color features, in which quotient space granularity computing theory applied to CBIR presented, Image retrieval is done by combined attribute features of quotient spaces and color features under different granularities.

3.2. Texture Features

Texture is a powerful spatial feature used for identifying objects or regions of interest by describing the spatial distribution of gray level variations in an image. Texture features capture the granularity and repetitive patterns of image surfaces and play an important role in image retrieval. Texture analysis is widely used in interpretation and classification of terrain images, radiographic and microscopic cell images. These features can be obtained spatially with statistical and pattern based features or from frequency domain using various transformation techniques. In this section we presented an overview of image retrieval using various textural features.

3.2.1. Statistical Texture Features

Mean, contrast, standard deviation, energy and entropy considered as statistical values to represent spatial distribution of pixels. In 1973 Haralick et al developed an angular nearest neighbor gray tone spatial dependence matrix to generate textural coefficients for describing the texture in a digital image [60]. In [216] texture feature of face image is calculated using GLCM matrix and minimum weighted Euclidean distance used for matching. In 1978 Tamura et al developed six parameters directionality, regularity, coarseness, roughness, line-likeness and contrast [184] for texture calculations. Texture almost mean coarseness. Contrast represent picture quality. Directionality is a regional property and considered as mono directional or bidirectional. Line likeliness describes the shape of the object. Regularity represent variations in of a placement rule. Roughness mainly chosen for tactile textures. These features got more popularity in CBIR as they optimum for human visual perception. Tamura texture features with fuzzy are used for CBIR in [99]. In [63] the textural features are obtained by calculating spatial relations in all eight directions. For optimal texture feature selection based on the classification problem, linear discrimination analysis is done in [65]. Texture classification based on texture spectrum presented in [197]. Block Difference Inverse Probabilities (BDIP) evaluates local brightness variation, BDIP is the mean difference of maximum intensity value with the intensity of the current pixel value with the ratio of maximum intensity value in that block. Block Variation of Local Correlation (BVLC) evaluate local texture smoothness by calculating the difference of maximum and minimum local correlation coefficients.

3.2.2. Discrete Cosine Transform based Texture

In this section we reviewed on texture feature exaction using DCT, DWT, Gabor, Ripplet and Curvelet transformations. Discrete Cosine transformation used to obtain energies of the image sub bands represented as features for image retrieval in citesmith1994transform. Discrete Cosine Transform (DCT) and its computation using FFT presented and performance of KLT and DCT compared in [3]. DCT got it at most usage in feature selection in pattern recognition and image processing. It is a popular transformation in JPEG image compression. In [13] DCT coefficients representing dominant directions and gray level variations are used as features with hierarchical similarity measure used for efficient retrieval. [109] image retrieval of JPEG images performed in frequency domain based on the DCT coefficients as features. Energy histograms of the low frequency DCT coefficients as features for image retrieval proposed in [109].

3.2.3. Wavelet Transform based Texture Features

An extensive survey has done on wavelets and analyzed the way of expressing any function in terms of integral of these states [66]. In [39] two different procedures for effecting a frequency analysis of a time-dependent signal locally in time are studied. The first is the short-time or windowed Fourier transform, the second is the wavelet transform, in which high-frequency components are studied with sharper time resolution than low frequency components. Gabor filters are group of wavelets with each wavelet capturing energy at a specific frequency and a specific direction, this leads to localized frequency description with which texture analysis can be done. Texture classification based on the energies of image sub bands proposed in [170], energies computed from wavelet sub band, DCT, uniform sub band and spatial partitioning. In [111] comparison of Gabor wavelet and orthogonal wavelet based texture features for texture classification and discrimination. [53] described about wavelets and their applications in various fields Also analyzed various other transformation techniques and compared Fast Fourier Transforms with Discrete Wavelet Transforms. [44] presented a wavelet based statistical texture retrieval method by modelling the marginal distribution of wavelet coefficients using generalized Gaussian density, and by computing Kullback-Leibler Distance among these GGDs with a maximum likelihood estimator. [6] used texture features by finding standard deviation of Gabor filtered image. [118] used affine transformations as a feature set for image retrieval. [187] used wavelet based spatial points for CBIR.

3.2.4. Operators/Pattern based Texture Features

Local Binary Pattern is used as a texture feature in image retrieval, as it is invariant to rotation and scaling. It is more robust and its implementation is computationally simple. These operators describes the spatial configuration of a local image texture and when combined with variance measures it is said to be more powerful tool for rotation invariant texture analysis. The first use of Local binary Patterns proposed in [129]. DFT of LBP histogram is a variant of LBP. It describes the texture pattern in a image and Fourier of LBP analyzes the joint relations between orientations of each pattern. In [182] query and database images are divided into non overlapping blocks and LBP histograms were computed and for each block Minkowski distance is used as a similarity measure which shown improved retrieval efficiency. [185] used Local Binary Patterns, Local Ternary Patterns for face recognition y including PCA based feature set based on Gabor wavelets and LBP. In [21] authors discussed about efficient feature descriptors and operators like Local Binary Patterns(LBP),Local Ternary Patterns (LTP), Local Derivative Patterns(LDP)and Local Tetra Patterns (LTTP) for image retrieval and used histogram intersection as a similarity measure. [164]Local Tetra pattern LTTP which uses 0 degree and 90 degree derivative of LDPs.i.e by calculating vertical and horizontal derivatives.

3.3. Shape Features

Shape features must be invariant to rotation, scaling and translation. These can be boundary based or region based. In this section we reviewed on various shape feature extraction techniques as moment invariants and descriptors. [108] reviewed on boundary based and interior/ region based shape analysis methods.

3.3.1. Region Based Shape Features

These features obtained by finding SADCT coefficients and are equal to the number of pixels in a given region, but they are capable to adapt to arbitrarily shaped regions. Its performance is almost same as orthogonalized methods. Compared with them SADCT can be implemented in real time and it does not require more computations like block DCT. Shape DCT algorithm proposed in [166] and easily incorporated into existing block based JPEG and MPEG coding schemes. Shape based CBIR in which grid based shape indexing presented in [156] and the proposed method compared with Fourier based and moment based techniques and shown improved retrieval. A combined corner edge descriptors to find regions with texture using autocorrelation functions [61].

3.3.2. Boundary Based Shape Features

Boundary based shape features including chain codes, Fourier descriptors and UNL Fourier features, interior based shape features using invariant moments, Zernike and pseudo Zernike moments along with combined feature based CBIR discussed in[115]. A shape similarity measure using Discrete curve evolution to simplify contours discussed in [102]. The user query can be given either by a graphical sketch or by an example silhouette. This measure establishes the best possible correspondence of boundary parts. In [70] two dimensional moment invariants proposed for geometrical shapes, Theoretical formulation and practical models based on moment invariants for visual pattern recognition were discussed. statistical pattern recognition is a core area for the implementation of multimedia data retrieval, face retrieval and character recognition and many other emerging applications. Pattern recognition techniques explored in Fukunaga. Fourier Descriptors are chosen for shape feature extraction as they are computationally less complex, easy normalization, more robust compared with other feature descriptors. Shape based CBIR using modified Fourier descriptors satisfying robustness and efficient feature extraction with spatial discretization of shapes proposed in [151]. Shape similarity measures based on local descriptors as features and M-tree index structure for effective CBIR proposed in [20]. [220] discussed retrieval results using Fourier descriptors (FD), curvature scale space (CSS)descriptors(CSSD),Zernike moment descriptors(ZMD) and grid descriptors (GD). The strengths and limitations of these methods are analyzed and clarified. In [16] a novel Fourier based approach WARP was used for matching and retrieving similar shapes, in this phase of Fourier coefficients are computed and the Dynamic Time Warping DTW distance was used to compare the distance between shapes. Generic Fourier Descriptors by computing 2-D Fourier transform over a polar shape used as shape features presented in [221] for CBIR. Edge Histogram Descriptors extract spatial distribution of edges. These are global or local, In local EHD image is subdivided into blocks and edge is determined from that block. In [132] importance of edge histogram descriptor for image similarity check in three levels as global, semi local and local histograms analyzed. Shape features based on edge histograms and Fourier transform coefficients of these edges in the polar coordinate system analyzed in [22]. [34] reviewed on existing edge and gradient based descriptors and shown Histograms of Oriented Gradient (HOG) descriptors worked well for human detection. Edge is a strong feature for characterizing an image. a robust technique to obtain edge map of an image with limited number of pixels and used as a global feature for CBIR presented in [15]. [222] reviewed shape representation techniques with their implementation procedures and advantages and drawbacks, identified promising techniques for shape feature representation. Zernike Moment Descriptors have multiple representation capabilities and invariant to basic geometrical transformations and less sensitive to noise, but lack in perceptual meaning. Scale and invariant point detectors presented in [118].

3.3.3. Transformation Based Shape Features

Ripplet transform is designed to represent images at different scales and directions. It is proven that this transform provide efficient representation of edges in images [207]. Ripplet transform is a higher dimensional generalization of curvelet transform, designed to represent 2-D signals at different scales and different directions. It can be a continuous Ripplet transform or discrete Ripplet transform. Ripplet transform used for feature extraction with a Multilayer perceptron neural network with Manhattan distance is used as a classifier in [157]. By using a K-mean retrieval threshold and cluster mean values by concentrating on size and shape values were used as features for image retrieval presented in [27]. Fractal is strongly related to shapes with self similarity. Fractal compression can be obtained from IFS theory based on Affine transformations, which is a combination of luminance transformation and geometrical transformation. Image retrieval using Fractal compression codes proposed in [163]. IFS code presented in [194]. The use of MPEG 7 descriptors for Self organizing maps (SOM) explored in [101]. A new shape descriptor for shape matching by computing correspondences between points on the two shapes with an aligning transform was proposed in [19]. A dynamic programming approach for shape matching proposed in [138] In this shapes of scaled images compared with original and open shape matches the whole or part of another open or closed shape, the method shown superior over Fourier descriptors and moments. [163] explores the use of fractal compressed code to retrieve similar images and also evaluated a fractal compressed code based retrieval along with its merits and demerits. The drawback of this approach is long compression time and lengthy compression codes, which is still need to be an open research issue. Affine invariant point detectors proposed in [116], [117].

3.4. Multiple Features

In Content Based Image Retrieval multiple features shown better retrieval efficiency rather single feature. In this section we presented the research done in image retrieval based on multiple feature extractions. The Virage search engine proposed in [12], used visual features used as image primitives and they can be very general or quite domain specific. Image retrieval based on color and shape attributes presented in [80]. The first and second order color moments and the color features in HSV space used in [103]. color and texture moments [215], [217]. Texture and shape features in [67], [178], color and texture in [31], [112], [153], in a histogram as color and edge directivity descriptor CEDD in [28], as Color Layout Descriptor CLD with Gabor textures in [82]. Image retrieval based on dynamic dominant visual features proposed [91], [145]. In [58]multi resolution histogram capturing spatial resolution was proposed. in this histograms are computed at multiple resolution levels, these are fast to compute, invariant to rigid moments and robust to noise and directly encodes spatial information. Selection of appropriate low level features based on a Genetic Algorithm that works on the basis of human visual perception presented in [146]. [165] presented CBIR with canonical features by performing Fisher score board and principal component analysis based selection of features and training of Bayesian and SVM classifiers accordingly. Performance comparison of feature subset selections given [57]. [42] quantitatively compared various features on four different datasets and detailed which features works good for a given data set. In [86] Image feature extraction and reduction techniques using Principal Component Analysis(PCA), Independent Component Analysis (ICA), Linear Discriminant Analysis (LDA) were discussed. Nearest neighbour and SVM classification techniques were analysed for similarity matching. Among all PCA with SVM shown better retrieval performance. [92] color histograms, Dominant color descriptors(DCD), edge histogram descriptors (EHD), Color Auto Correlogram (CAC), Block Difference of Inverse Probability (BDIP), Block Variation of Local Correlation (BVLC) coefficients, and color Difference Histogram (CDH) performances were analysed. color histogram shown better performance in HSV space. Dominant Color Descriptor shown good results in RGB space. for color correlogram, HSV space worked better than RGB space.

4. SIMILARITY MEASURES

Efficiency of Content Based Image Retrieval process not only depends on best visual feature extraction techniques but also on proper selection of similarity measures. In this section we glimpsed various distance metrics used for different visual cues in image retrieval. Euclidean Distance is one of the most popular distance metric. Euclidean distance measures analysis in fractal coded image features proposed in [163]. Minkowski distance metric is generalized form of Euclidean distance and city block distances, preferred when each dimension holds equal importance in retrieval process. It was used in [8] for feature vector comparison. [182]used L1 metric Minkowski distance to compare LBP histograms of query and database images. Manhattan distance measure also known as city block distance and it depends on the rotation of the coordinate system, rather its translation. Used in [157]. Bhattacharya distance metric measures the statistical separability between spectral classes, proposed by [50]. Fourier descriptors compared with Bhattacharya distance in [153]. Kullback - Leibler distance for texture features discussed in [44]. In 1936 P.C. Mahalanobis developed Mahalanobis distance metric. By using this different patterns can be determined. Quadratic form distance works on the cross similarity between dominant colors. With this retrieval efficiency improved. Earth movers distance and hybrid feature including color, texture and shape as feature vector to match image in [219]. Chi - Squared distance is used in [18] to compare two binned data sets and also determine if they are drawn from the same distribution function. The distance between color sets obtained with the walk distance in HSV color space [171]. [171] used histogram Euclidean and histogram quadratic distances. VisualSEEk system for finding the images with most similar arrangements of similar regions by automatically extracting and indexing color regions described in [172]. In anchoring, objects are represented by distances between known anchors, image similarity is obtained as a function of distances from representative images which reduces dimension of similarity measurement [125]. Extended distance functions d1 d2 d3 for comparing R Histograms proposed in [200]. [16] used Dynamic Time Warping distance for exact matching image shapes even in the presence of phase shifting. Histogram intersection is an efficient way of matching histograms. In [181] proposed histogram intersection for similarity measurement between two color histograms. The paper also proposed an algorithm called incremental intersection in which only largest bins are compared and it is implemented in two phases-off line and online. Histogram intersection is used as a similarity measure in [92]. In [153] YCbCr histograms compared with histogram intersection. Normalized Rank Sum similarity measure used for retrieval performance evaluation for CBIR in [59]. Fuzzy Hamming Distance to compare two color histograms that include color difference along with the amount of magnitudes discussed in [78].

5. FEATURE INDEXING AND CLASSIFICATION

Feature dimensionality reduction achieved with proper feature selection and subspace learning. An image represented by a number of possibly correlated variables as its features, when mapped into a smaller number of variables known as principal components [148]. [54] presented a joint feature selection and subspace learning on face recognition dataset. Generalized fisher score for feature selection presented in [55]. Fisher Discrimination analysis used for feature set reduction [170]. In this section we discuss feature indexing techniques and feature space learning techniques using SVMs, neural networks and Fuzzy systems.

5.1. Image Feature Indexing

In this section we reviewed image indexing techniques available in literature using clustering, self organizing maps and non parametric techniques. Shape indexing by arranging shape tokens in M-tree index structure and comparative analysis of different indexing schemes presented in [20]. [27] implemented a k-mean clustering method for image retrieval. This method concentrates on shape and size similarities. Images with similar threshold values got clustered, and the query image is compared with the cluster mean value. For the analysis of multi model feature space a non parametric technique mean shift with the equivalence to the Nadaraya Watson estimator from kernel regression and the robust M estimators of location to delineate shaped clusters was established in [33]. A new indexing scheme based on Self Organizing Maps presented in [101]. Wide range of aspects for feature set construction, ranking and multivariate feature selections presented in [57]. Leader clustering based indexing presented in [97] to use in FIRST system. In [72] image indexing using color correlogram combined with supervised learning methods for metric and query.

5.2. Classifications

5.2.1. Support Vector Machines

In [201] reviewed on Support Vector Machines and best feature selections for SVM. Learning relevant and non relevant using SVM in large databases presented in [223]. Automatic selection of multiple parameters for support vector machines by using a gradient descent algorithm presented in [26]. In SVM based RF approaches SVM classifiers are unstable for small training samples to overcome this multi training SVM developed in [106]. Primal optimization of non linear SVM and update rules for Newton optimization derived in [25]. Support Vector Machines used in CBIR to learn high level concepts from low level features. [152]. [6] proposed a frame work for CBIR in which Gabor filter is used for feature extraction and trained SVM Classifier with these Gabor coefficients, to retrieve the similar images. Method compared the performance with Gabor features and Euclidean distance and Gabor features with SVM on WANG and COIL image databases and proved SVM improved retrieval. The canonical feature set is partitioned into four distinct features sets as feature combinations and their transformations. Later principal component analysis and fisher score based selections are done for feature optimization. In fisher score based feature selection the features of all classes were concatenated one below the other and score is given to each of them based on their mean and standard deviation. All these scores arranged in descending order and features with high scores got selected. these reduced features are used to train Bayesian and SVM classifiers and the performance of classifiers analyzed and observed that SVM classifier shown better performance over Bayesian classifier.

5.2.2. Neural Networks

A Multilayer perceptron neural network with Manhattan distance used as a classifier in [157]. An unsupervised and supervised texture classification of Brodatz natural texture images by using a texture spectrum presented in [64]. In [72] image indexing using color correlogram combined with supervised learning methods for metric and query. A neural network is trained on queries rather database images in [98]. [79] used a K-nearest neighbor classifier to retrieve the images that contain manmade objects, features were generated by strong boundaries. [131] presented image classification using compound image transforms. [54]proposed a joint feature selection and subspace learning with L2,1 norm on the projection matrix for obtaining row sparsity. In[91]used a Probabilistic Neural Network was used as classifier. [165] talks about comparative analysis of classifiers with extraction of discrete feature sets from a set of canonical features and these features are obtained by using WND-CHARM tool. An unsupervised and supervised texture classification of Brodatz natural texture images by using a texture spectrum presented in [64]. A neural network is trained on queries rather database images in [98]. [79] used a K-nearest neighbour classifier to retrieve the images that contain manmade objects, features were generated by strong boundaries. [131] presented image classification using compound image transforms. [54]proposed a joint feature selection and subspace learning with L2,1 norm on the projection matrix for obtaining row sparsity. In [6] SVM Classifier trained with Gabor coefficients to retrieve the similar images. Supervised learning have the properties of Margin maximization and Kernel trick.

5.2.3. Fuzzy Logic in Content Based Image Retrieval

A fuzzy set is a class of objects with a continuum of grades of membership ranging from 0 to 1. Fuzzy logic is developed to interpret the natural expressions as different membership functions, then the neural network is designed to learn the meanings of membership functions. A binary search algorithm is used for matching and retrieval. Fuzzy sets used in CBIR for best feature selection to reduce the semantic gap and combined with neural networks for achieving automatic image classifications. In this section we presented how CBIR gets effected with the inclusion of Fuzzy. [218] is the first paper on fuzzy sets and discussed their usage for any application domain. A hybrid approach for CBIR using neuro-fuzzy technique proposed in [98]. To overcome the problem of imprecision of the pixel color values, fuzzy color histograms with corresponding fuzzy distances (Bhattacharya distance) proposed as a color descriptor for content based image retrieval in [193]. Fuzzy color histograms with L1 distance metric presented in [192] to overcome the uncertainty arising from quantization of colors and human perception of colors. Region based image retrieval using fuzzy features to denote color shape and texture properties of a segment and Unified Feature Matching (UFM) as a similarity measure to compare the fuzzy families presented in [30]. To perform image retrieval over large image databases conventional histograms have large dimensions and need more computational time and they cannot consider the color similarities and dissimilarities among the bins. To overcome this a novel and fast approach in computing membership values based on Fuzzy c means algorithm proposed in [59] to generate Fuzzy Color Histograms (FCH) by considering color similarity of each pixel with all other bins using a fuzzy membership function. In [14] CBIR using fuzzy edge map thresholded at different levels of an image was presented, the method worked well with singe object images with non textured backgrounds. Fuzzy membership applied for similarity measure in achieving image retrieval Fuzzy Hamming Distance was used in [78] as a similarity measure between two color histograms, with this context similarity was also verified to reduce the semantic gap. A new CBIR called Fuzzy Image Retrieval SysTem (FIRST) in [97] used fuzzy attributed relational graphs (FARGs) to represent images, where each node in the graph represents an image region and each edge represents a relation between two regions. The given query is converted to a FARG, and a low complexity fuzzy graph matching algorithm is used to compare the query graph with the FARGs in the database. Average Area Histogram AAH with fuzzy based similarity measures, fuzzy based weight updations of features and subjectivity of human perceptions by fuzzy rules for color and shape features got the improvement in retrieval efficiency. [206] To overcome the semantic gap between high level concepts with low level features, [2] proposed a graph matching approach by representing objects of an image as Fuzzy Attributed Relational Graphs (FARG) to represent the human thinking process by allowing the query to be given in words. Fuzzy based KNN classifications for generating semantic metadata that describe spatial relationships between objects proposed in [200]. these spatial relationships denoted by R-Histograms and given as input to a set of Fuzzy KNN classifiers. Query Vector Modification with Fuzzy relevance feedback with six relevance levels proposed in [202]. Image similarity computed by Euclidean distance for or twelve color features of Itten color wheel. To minimize the semantic gap in CBIR fuzzy logic implemented in natural language based queries and a fuzzy based similarity measure proposed in [99].

6. SEMANTIC CBIR

Though evaluation of CBIR has done four decades back still it is finding the difficulties to retrieve semantically similar images based on low level visual features. Hence the researchers started looking for alternative ways for improving the performance of CBIR. This resulted in usage of relevance feedback, knowledge based, SURF and SIFT features and other semantic models. In this section we presented how recent CBIR techniques overcome the sensory gap with inclusion of semantics with existing low level attributes. In [56] a new layered data model and the design of query processing unit presented. In [214] proposed a system of multimedia content based retrieval and querying based on audio and visual characteristics. [69] proposed querying and content based retrieval by consideringaudioorvisualpropertiesofmultimediadata.HSV color space provide better relations between color similarities and dissimilarities and finding correlograms in this space provide more color sensitiveness rather illumination. In [128] retrieval performance of HSV correlograms compared with RGB correlograms and queries with eight semantic categories of images. [104] proposed distance functions for perceptual similarity for color, shape and spatial distribution. Two latent space models Latent Semantic Analysis and Probabilistic LSA used to define keywords for images presented in [121]. In [46] presented a semantic interactive retrieval by describing the visual and conceptual contents in the form of SVM based relevance feedback method. Ontologies represent domain concepts and relations in a form of semantic network. An ontology can be build based on the low level features and the domain knowledge of canine. Multi-modality ontology model proposed to integrate high level semantic concepts in the form of text with low level image features with this intelligent image retrieval is achieved. [195]. Semantic web based frame work for automatic feature extraction, storage, indexing and retrieval of videos with a new ranking algorithm presented in [160] . In [62] described the use of visual data, textual data in the form of context information, and user interaction in the image retrieval process. In [36] fusion of salient methods worked well for image retrieval rather individual saliency methods.

6.1. Relevance Feedback

Relevance feedback is a simple and powerful technique to retrieve semantically similar images. [72] presented effect of relevance feedback with color correlogram as feature in image retrieval. [149], [150] proposed a relevance feedback based interactive retrieval approach in which user high level query and perception subjectivity were captured by dynamically updated weights based on the users relevance feedback. [224] explore the uniqueness of the relevance feedback along with its merits and implementations and offered novel solutions. CBIR with adaptive classification and cluster merging to find multiple clusters of a complex image query for learning enhanced relevance feedback proposed in [37], [96] over viewed on the CBIR approaches with relevance feedback on feature re-weighting and instance based Relevance Scored Method RSM worked better over Feature Reweighting method (FRM). Images ranked according to a relevance score depending on nearest neighbor distances in low level feature spaces and in dissimilarity spaces proposed in [51]. Different relevance feedback algorithms and their performances analyzed in [87], [168] presented the integration of relevance feedback techniques and region based image retrieval to improve the accuracy of CBIR.

6.2. Special Features

Bag of visual words In bag of visual words approach an image is represented as an unsorted collection of local descriptors that use only the intensity information and the resulting model provides little insight about color spatial information of the image. A Novel image representation method using Gaussian Mixture Model (GMM) to provide spatial weighting for visual words and applied this for CBIR. the cosine similarity used as distance measure between spatial weighted visual word vectors. [29]. Spatial weighting scheme based on local patch extraction and fusion of descriptors for bag of visual words developed in [45]. In [188] distance and weighting schemes for bag of visual words presented. Locality sensitive hashing, SR tree based indexing and naive L1 and L2 norm based distance metric calculation based indexing techniques explored in [122].

7. Conclusion

In this paper we presented an exhaustive literature review of CBIR from its inception to till date. We reviewed on benchmark image databases, color spaces, visual attributes of image as color, texture and shape features and combination of these. Spatial and frequency domain based feature extraction methods and similarity measures applied in the process of retrieval. We also reviewed on feature reduction, indexing along with various neural network classifiers, SVMs and Fuzzy systems with their effect in retrieval process, effect of relevance feedback and its importance in semantic image retrieval. This survey paper can be viewed as an exhaustive literature review of CBIR in various aspects from its origin to the new age.

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