Content-Based Image Retrieval: The State of the Art

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Content-Based Image Retrieval (CBIR) is the solution to the image retrieval problem based on the contents of the query image. The objective of the CBIR system is to retrieve the visually similar images from the database efficiently and effectively but still, no satisfactory performance has been achieved. The performance of the CBIR system mainly depends on the feature extraction, feature selection, distance measures (similarity computation), Classification, and ranking of matched images. Feature extraction is the procedure of deriving the set of features from images for matching the visual similarity and they can be further classified based on color, texture, and shape descriptors. Performance is not up to mark when Color, Texture or Shape descriptors individually applied. Better determination of blend of Color, Texture, and/or Shape features can enhance performance in the context of precision and recall. This paper mainly concentrates on the brief review of the different state of art techniques used for CBIR along with prerequisite knowledge over this domain.

Keywords: TBIR, CBIR, Feature Extraction, Feature Selection, Distance Measure, Ranking.

1. INTRODUCTION

IMAGE retrieval is defined as the retrieval of semantically relevant images from a database of images. The requirement of retrieving similar images from a large database is the need of an hour (Mary, Vasuki, & Manimekalai, 2017). Images can be retrieved based on the metadata or content of the query image. It can be classified based on the specified query. Retrieving the images based on the query from a large database is not an easy task when you are using a traditional approach like *Text Based Image Retrieval (TBIR)* where the search is based on automatic or manual annotation of images. Because in TBIR, idea is to retrieve the images from the database based on the metadata of the image. So, the problem of annotation of the image and laboring cost arises. Some other factors that lead us to *Content-Based Image Retrieval (CBIR)* are: (i) Manual or automatic annotation of images based on metadata (Y. Rui, Huang, & Chang, 1999), (ii) Too much responsibility on the end user and also it's subjective to the human perception (Liu, Zhang, Lu, & Ma, 2007), (iii) Queries that cannot be described at all, but tap into the visual features (Liu et al., 2007).

To overcome the above disadvantages of text-based retrieval system, CBIR was introduced in the early 1980s (Liu et al., 2007). CBIR, also known as Query By Image Content (QBIC) is an automated technique that takes an image as a query and returns a set of images similar to the query from the large set of database images (Tyagi, 2017). The query image is converted into the internal representation of feature vector using various feature extraction techniques. In CBIR, images are indexed by their visual content, such as color, texture, shapes and spatial information. Though many sophisticated algorithms have been designed to describe color, shape, and texture features, these algorithms cannot adequately model image semantics and have many limitations when dealing with broad content image databases (Liu et al., 2007). Netra, QBIC, SIMPLIcity, MetaSEEK, VisualSeek, Blobworld, PicHunter, Google Image Search, Camfind, Pixolution, and DRAWSEARCH are some known content-based image retrieval systems (Tyagi, 2017). 'Jet.com - an elasticsearch based E-Commerce' is one of the innovative examples of using CBIR for textual queries of customers. PictPicks (Google's material design interface) and Veracity (reverse image search on iOS) are also some other examples of CBIR. The automatic derivation of semantically meaningful information from the content of an image is the focus of interest for most research on image databases. It's been a wide area for research from the last decade. Retrieving a semantically relevant image from a large set of images is not an easy task. Because it's impossible to decide any single technique from a bunch of techniques to retrieve better relevancy.

Challenges like *semantic gap* and *intention gap* are issues in current CBIR systems. A difficulty that a user suffers to precisely express the expected visual content by a query at hand is called intention gap. Another is the semantic gap originates from the difficulty in describing a high-level semantic concept with low-level visual features (Liu et al., 2007; Tyagi, 2017; W. Zhou, Li, & Tian, 2017). Image retrieval problem is alive because of not availability of satisfactory retrieval results and this is an era of science and computing and after all, challenges are boon to discovery. Let's discuss some of the open challenges in CBIR. Firstly, no single feature extraction technique can provide all the robust features. Deciding set of feature extraction techniques for CBIR is a vital task. Second is selecting the low number of handy features from the set of extracted features. Different dimensionality reduction techniques like Principal Component Analysis (PCA) (Jolliffe, 2011), Non-negative Matrix Factorization (NMF) (D. D. Lee & Seung, 1999), and Independent Component Analysis (ICA) (Comon, 1994) can be used for reducing the size of the feature. Then, robust features can be selected by using Linear Discriminant Analysis (LDA) (Xu, Yan, Tao, Lin, & Zhang, 2007), Genetic Algorithm, and/or other feature selection techniques. Feature selection strategies can be taken from Evolutionary Computing (EC), Swarm Optimization (SO), and Artificial Intelligence (AI). The third point which can be discussed is matching similarity in between images. It can be done by using template matcher or machine learning classifiers. In the last, we must focus on the ranking of the images because after all, the user is only interested in the range of visually similar images. Furthermore, achieving high precision and recall for large datasets is also a challenging task.

CBIR Applications: *Art Collections* (Ivanova & Stanchev, 2009; Holt & Hartwick, 1994; Long, Antani, Deserno, & Thoma, 2009), *Crime Prevention* (Liu, Huang, & Gao, 2014; Liu, Huang, Zhang, Zhang, & Ling, 2017; Shriram, Priyadarsini, & Baskar, 2015), *Geographical Information And Remote Sensing Systems* (Joshi, Purohit, & Mukherjee, 2017; Hafiane, Chaudhuri, Seetharaman, & Zavidovique, 2006), *Intellectual property* (A. Tiwari & Bansal, 2004; Vrochidis, 2008; Zhu et al., 2011; List, 2007), *Medical* (X. S. Zhou et al., 2008; Antani, Long, & Thoma, 2008; Chuctaya et al., 2011; Ruiz, 2006; Jones, Schaefer, & Zhu, 2004; Shyu, Kak, Brodley, & Broderick, 1999) *Military and Defence* (Merwe, Ferreira, & Clarke, 2005), *Photograph Archives and Retail Catalogs* (Colombo & Alberto, 2002; Enser, Sandom, & Lewis, 2005; Graham, 2001), *Nudity-Detection Filters* (Choras, 2010; Lopes, de Avila, Peixoto, Oliveira, & de A Araujo, 2009; Lopes, de Avila, Peixoto, Oliveira, de A Araujo, & de M Coelho, 2009), *Face Finding Systems* (N. Kumar, Berg, Belhumeur, & Nayar, 2011; Abate, Nappi, Ricciardi, & Tortora, 2004; L. Zhang, Hu, Li, Ma, & Zhang, 2004).

The rest of the paper explains CBIR General Framework, Feature Extraction, Feature Selection, Comparative study of different CBIR techniques, Similarity Computation, and so on. In the last section, critical reviews are deduced.

2. LITERATURE SURVEY

Initial text-based approach has been altered by CBIR to enhance the accuracy (Mary et al., 2017). CBIR has become an important research topic due to its increased availability of bandwidth. CBIR General Framework is shown below in Figure 1.

In CBIR, the visual contents of the images in the database are chosen and described by multidimensional feature vectors. As shown in Figure 1, CBIR system contains query processing module which accepts the query and information from the user for processing. Then, Feature Vectors are generated from the query image and database images by using various feature extraction methods in order to find visual similarity. Various distance measures are used for calculating the similarity between the query and the database images. Then, most relevant results are produced using ranking methods and shown to the user. Recent retrieval systems have integrated user's relevance feedback to change the retrieval activity in order to generate perceptually and semantically more meaningful retrieval results (Tyagi, 2017).

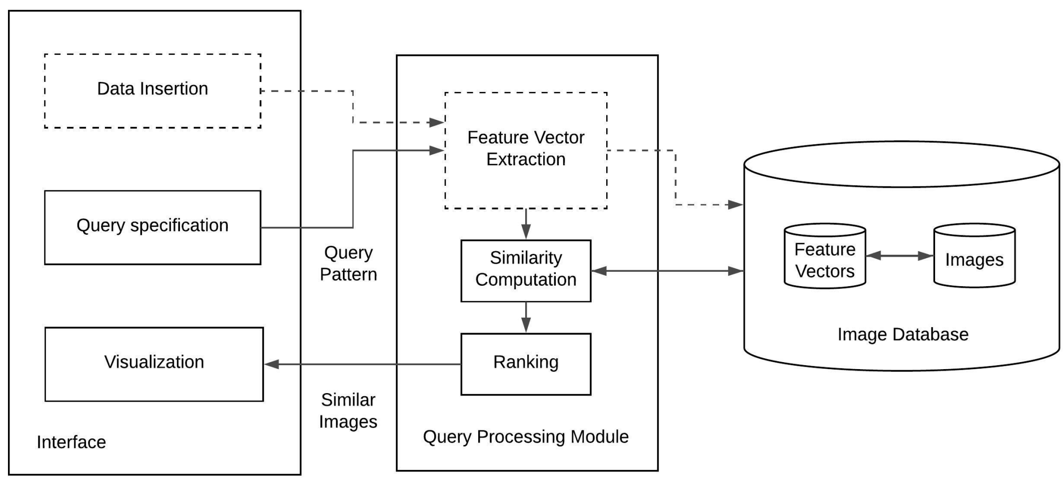

Figure 1: CBIR General Framework

As mentioned by Eakins, Graham, and Franklin (1999), there are three levels of queries in CBIR : (i) *Level 1* - Retrieval by primitive features of images like such as color, texture, shape or the spatial information. A typical query example can be, 'find images like that'. (ii) *Level 2* - Retrieval based on derived features, with some degree of logical inference. An example can be like, 'find an image of a fountain'. (iii) *Level 3* - Retrieval by abstract attributes, with some degree of high-level reasoning about particular item or object. This includes retrieval of named circumstances, where pictures contain emotive or devout content, etc. Example of a query can be like, 'find images of a laughing little girl'. Levels 2 and 3 together are referred to as *Sementic Based Image Retrieval (SBIR)*, and the gap between Levels 1 and 2 as the semantic gap Tyagi (2017).

In a survey, Liu et al. (2007) have categorized the state-of-the-art techniques in reducing the 'semantic gap' in five categories: (1) Using object ontology to define high-level concepts, (2) Using machine learning tools to associate low-level features with query concepts, (3) Introducing relevance feedback (RF) into retrieval loop for continuous learning of user's intention, (4) Generating semantic template (ST) to support high-level image retrieval, and (5) Making use of both the visual content of images and the textual information obtained from the Web for WWW (the Web) image retrieval.

2.1 Feature Extraction

A key function in any CBIR system is the feature extraction. Feature extraction is the process of mapping the image pixels into the feature space. A feature is a piece of information. To distinguish two images from one another, the extraction of visual information is the most required thing. Feature extraction converts the input images into a set of feature values or feature vectors (Y. Rui et al., 1999). More generally they provide values for finding visual similarity.
There are mainly four types of feature that can provide characteristics of an image : (i) Color, (ii) Texture, (iii) Shape, (iv) Spatial information. Those features that can be extracted automatically

from the image without any spatial information are known as low-level features. Color, Texture and Shape descriptors are low-level features of the image. Feature extraction methods broadly fall in two categories viz. global methods and local methods. In *global methods*, feature extraction process considers complete image, whereas in *local methods* some portion of image is taken in account for extracting features.

2.1.1 *Color Representation.* Among the visual features, color is the most vital, reliable and widely used feature. Most commonly used color descriptors are color moments, color histograms, color coherence vector, and color correlogram. Color plays a very important role in human visual perception mechanism. All methods for representing a color feature of an image can be classified into three groups: color histograms and statistical methods of color representation and MPEG-7 (The Moving Picture Experts Group-7) descriptors.

MPEG- 7 is a standard developed by MPEG (Moving Picture Experts Group). The MPEG-7 standard, formally named "Multimedia Content Description Interface", provides a rich set of standardized tools to describe multimedia content and supports content-based multimedia management. Classification of Color Representation of different descriptors is shown in Table. I.

Table I: Color Representation

Histogram Based Methods	Global Color Histogram (K. L. Rao, Rao, & Reddy, 2016; Boparai & Chhabra, 2015) Histogram Intersection (Srivastava, Wadhvani, & Gyanchandani, 2015) Local Color Histogram (Pass & Zabith, 1996) Color Histogram For K Means (CHKM) (Srivastava et al., 2015) Color Difference Histogram (Srivastava et al., 2015) Color Histogram Using GLCM (Rasli, Muda, Yusof, & Juhaida, 2012)
Statistical Methods	Color Co-occurrence Matrix (Jhanwar, Chaudhuri, Seetharaman, & Zavidovique, 2004) Color Correlogram (Huang, Kumar, & Mitra, 1997; Jing, Kumar, Mitra, Zhu, & Zabih, 1997) Color Coherence Vector (Pass & Zabith, 1996) Color Moments (Stricker & Orengo, 1995) Color Sets (Smith & Chang, 1996) Color Signature (Alsmadi, Omar, & Noah, 2011)
MPEG-7 Color Descriptors	Dominant Color Descriptor (Shao, Wu, Cui, & Zhang, 2008; M. Rui & Cheng, 2009; Talib, Mahmuddin, Husni, & George, 2013; Y.-H. Lee & Kim, 2015) Scalable Color Descriptor (Tyagi, 2017) Color Structure Descriptor (Tyagi, 2017) Color Layout Descriptor (Tyagi, 2017)

Manjunath, Ohm, Vasudevan, and Yamada (2001), used CIE LUV color space and Generalized Loyd Algorithm to quantize colors for Dominant Color Descriptors (DCD) and it was experimented on 2500 images of Corel database by the author. Wong, Po, and Cheung (2006), also used DCD but they improved the performance of it by combining it with another MPEG-7 descriptor Color Structure Descriptor (CSD). As per the results provided by DCD with Generalized Loyd Algorithm are not consistent with human perception as shown by Yang, Kuo, Chang, Lee, et al. (2008). The distance Equation should be a function that not only depends on the percentages of dominant colors but also depends on the number of dominant colors. To overcome this issue, Yang et al. (2008) used Linear Block Algorithm (LBA) for color quantization and introduced a modification in dissimilarity measure used for DCD.

Furthermore, Islam, Zhang, and Lu (2008) used DCD with vector quantization Automatic Categorization of Image Regions using color descriptors and the algorithm was guided by a novel splitting and stopping criterion. M. Rui and Cheng (2009) provided efficient color image retrieval using DCD and for classification, they proposed Fuzzy Support Vector Machines (FSVM). Li and Bao (2010) proposed a method of extracting image dominant color based on region growing algorithm in his paper. The author used HSV color space for his work and he compared the results to the Merged Histogram based method proposed by wong. Talib et al. (2013) proposed weighted DCD in his paper. More work was shown in the paper of Walia, Saigal, and Pal (2014) by using Modified LBA for better quantization of the color space. And they used Corel-10k and Wang dataset as per reference to their paper. Boparai and Chhabra (2015) used HSV Color Histogram and Color Moments as Color descriptor in his paper and used a hybrid approach by blending it with wavelet transform and Zernike Moment. Soni and Mathai (2015) proposed a method combining Color Histogram and Color Correlogram in their paper in order to enhance performance. In that paper, they compared the results with Color Histogram, and proposed approach works fine. The implementation was done using wang dataset. K. L. Rao et al. (2016) used Color Histogram for RGB color description.

Mary et al. (2017) used Color Moments as a color descriptor in their paper and combined it with Gray Level Co-occurrence Matrix (GLCM) and Fourier Descriptor. In Effat and Kumar (2017) used Color Moments and blended it with other texture and shape descriptors but focus on mainly on machine learning techniques like K-Means clustering, and Neural Network along with genetic algorithm.

A review on color feature extraction is given in the review paper of Alphonsa and Sreekumar (2014) and also in the survey paper of Srivastava et al. (2015).

Pre-processing on the image can be done using color segmentation Khattab, Ebied, Hussein, and Tolba (2014); Monika and Agnes (2013) and color quantization to achieve better discrimination between the images.

Color Quantization: Color quantization is the process of reducing the number of colors in a digital image. The main objective of the quantization process is that significant information should be preserved while reducing the color of an image. The main purpose of Color Segmentation is to reduce the number of colors available in the image in order to get a better color representation of the image so that better discrimination can be made. Different strategies were used with different color descriptors.

Manjunath et al. (2001) used Generalized Lloyd Algorithm in his paper to quantize CIELAB color space. Islam et al. (2008) used Modified Vector Quantization for HSV color space. M. Rui and Cheng (2009) used Graph-Theoretic Algorithm for quantization of HSV color space for DCD. Li and Bao (2010) used Region Growing Algorithm for quantization for DCD. Walia et al. (2014) proposed DCD with Modified Linear Block Algorithm (LBA) in order to enhance the performance of CBIR. Fadaei, Amirfattahi, and Ahmadzadeh (2017) used HSV color space quantization by dividing the HSV color space in 8 parts. Yang et al. (2008) used Linear Block Algorithm (LBA) for quantizing color space. Color Quantization let us reduce the number of colors which decreases the complexity of the color feature vector descriptor.

Color Segmentation: Color segmentation is based on the color feature of image pixels assumes that homogeneous colors in the image correspond to separate clusters and hence meaningful objects in the image. In other words, each cluster defines a class of pixels that share similar color properties. As the segmentation results depend on the used color space, there is no single color space that can provide acceptable results for all kind of images Khattab et al. (2014).

2.1.2 *Texture Feature Representation.* The Texture is an important property of the image which is usually defined as visual appearance or tactile characteristics of the objects in the image. It mainly comprises the elements of texture primitives (i.e., texture elements or texels) arranged in some specified order (i.e., texture layout). The notion of a texel is central to texture. Texture descriptors mainly classified in: (i) Perceptual Model, (ii) Statistical Model, (iii) Structural Model, (i) Transform Model. Differnt descriptors for Texture are as per shown in Table. II.

Grey Level Co-occurrence Matrices (GLCM) proposed by Haralick (Haralick & Shanmugam, 1973) is one of the methods for representing texture features of images. Spatial patterns like Local Binary Patterns (LBP) (Ojala et al., 2002), Local Directional Patterns (LDP) (Jabid et al., 2010), Local Ternary Patterns (LTP) (Tan & Triggs, 2007), Local Tetra Pattens (LTrP)

Table II: Texture Representation

Perceptual Model	Tamura Features (Tyagi, 2017) Wold Features (Tyagi, 2017)
Statistical Model	GLCM (A. S. Rao, Krishna, & Krishna, 2015) Laws Energy Feature Autocorrelation Spatial Patterns - Local Binary Patterns (LBP) (Ojala, Pietikainen, & Maenpaa, 2002; Khare & Srivastava, 2017), Multi-Scale LBP (Khare & Srivastava, 2017), Local Directional Patterns (LDP) (Jabid, Kabir, & Chae, 2010), Local Ternary Patterns (LTP) (Tan & Triggs, 2007), Local Tetra Patterns (LTrP) (Murala, Maheshwari, & Balasubramanian, 2012; T. G. S. Kumar & Nagarajan, 2018), Local Mesh Patterns (LMeP) (K. L. Rao et al., 2016), Local Quantized Patterns (LQP) (K. L. Rao et al., 2016), and etc. SURF (Y.-H. Lee & Kim, 2015) SIFT
Structural Model	Voronoi Diagram (Tao & Grosky, 1999)
Transform Model	Curvelet Transform (Fadaei et al., 2017) Gabor Transform (Boparai & Chhabra, 2015) K-L Transform (Tyagi, 2017) R Transform (Wang, Huang, & Tan, 2007) Wavelet Transform (Fadaei et al., 2017)

(Murala et al., 2012) are still famous in the area of CBIR. A large amount of research work is done on Local Binary Patterns.

Takala, Ahonen, and Pietikainen (2005) proposed block-based texture methods over LBP for CBIR. They introduced two different approaches. The first method divides the query and database images into equally sized blocks from which LBP histograms are extracted. The second approach uses the image division on database images and calculates a single feature histogram for the query.

The main reason that these approaches become so popular is their easiness on feature extraction stage and supremacy on the feature classification performance. Tan and Triggs (2007) proposed LTP descriptor for face recognition which is more discriminant and less sensitive to noise as compared to LBP. Authors extended LBP to three quantized values -1, 0, 1 instead of considering only two values 0, 1. Jabid et al. (2010) proposed Local Directional Patterns for texture description to overcome the issue of LBP Ojala et al. (2002) of not considering directions for feature extraction.

Murala et al. (2012) proposed Local Tetra Pattern (LTrP) which describes the spatial structure of the local texture using the direction of the center gray pixel. They experimented it on Corel 1000 database, Brodatz texture database, and MIT VisTex.

Vipparthi and Nagar (2014) proposed a new color-texture descriptor Color Directional Local Quinary Patterns (CDLQP) for Content-Based Indexing and Retrieval. It extracts the individual R, G and B channel wise directional edge information between reference pixel and its surrounding neighborhoods by computing its grey-level difference based on quinary value (2, -1, 0, 1, 2) instead of binary and ternary value in $0°, 45°, 90°$, and $135°$ directions of an image which are not present in literature (LBP Ojala et al. (2002), LTP (Tan & Triggs, 2007), CS-LBP, LTrPs Murala et al. (2012), etc.). And an conducted experiment on Corel-5000 and MIT-Color database.

T. S. Kumar and Nagarajan (2015) proposed Local Smoothness Pattern (LSP) in their paper. The idea of LSP is to follow the smooth regions so that the smoothness over the curves can be captured. It was tested on Brodatz datasets. It performs better than LBP Ojala et al. (2002) as per the results of the paper shows. Later on, authors also introduced Local Curve Pattern (LCP) in their other paper in the year of (2018) for texture descriptor. LCP technique uses image line/curve characteristics to derive the local pattern. Implementation was done Corel 1K, Corel 10K and Brodatz. The results of the paper show that it outshines when compared it with other patterns like LTrp Murala et al. (2012), BOF-LBP (local binary pattern with bag-of-filters), and DBWP (directional binary wavelet pattern).

K. L. Rao et al. (2016) proposed new texture feature descriptor Local Mesh Quantized Extrema Pattern for CBIR and they combined it with RGB color Histogram for enhancing performance and experimented on MIT VisTex and Corel-1k databases.

Lu and Huang (2016) proposed Improved LBP (ILBP) descriptor for texture description. The proposed ILBP based on pattern uniformity measure and the number of ones in the LBP codes. ILBP is invariant in terms of monotonic gray-scale change, histogram equalization operation, and rotation transformation. A major advantage of ILBP over traditional LBP is that it detects a large group of local primitives from non-uniform patterns. They used Outex and RotInv_16_10 datasets for an experiment.

Recent work on Multiscale Local Binary Pattern (MS-LBP) is done by Khare and Srivastava (2017). In this paper, the authors proposed another strategy for implementing MS-LBP in order to improve performance. This scheme overcomes the limitations of single scale LBP and acts as the more robust feature descriptor.

A. K. Tiwari, Kanhangad, and Pachori (2017) proposed a histogram feature refinement methods for enhancing the performance of texture descriptor based content-based image retrieval (CBIR) systems. In the proposed approach for histogram refinement, each pixel in the query and database images is classified into one of the two categories based on the analysis of pixel values in its neighborhood. In this paper, Histogram refinement is applied on many spatial patterns like LBP (Ojala et al., 2002), LDP (Jabid et al., 2010), LTP (Tan & Triggs, 2007), LTrp (Murala et al., 2012), and etc.

Fadaei et al. (2017) used Wavelet and Curvelet as texture descriptor in their paper and combined it with DCD (Dominant Color Descriptor).

Chang, Xiaoyang, Xiaoming, and Boyang (2017) used SIFT (Scale Invariant Feature Transform) along with another state of art method DAISY which needs about only one-tenth of the number of computational operations of SIFT descriptors. DAISY is essentially similar to SIFT, except that uses a Gaussian kernel to aggregate the gradient histograms in different bins whereas SIFT relies on a triangularly shaped kernel. SIFT descriptors outshine when compared to DAISY descriptor.

W. Zhou, Li, Sun, and Tian (2018) used SIFT descriptor however work was focused on the indexing mechanism. In that paper, they introduced a new image indexing using SIFT and CNN (Convolution Neural Network). They used the algorithm on two public benchmark datasets, i.e., the UKBench dataset and the Holidays dataset.

2.1.3 *Shape Feature Representation.* The shape of an object is an important and basic visual feature that can describe image content. In the context of CBIR, the word shape is used to refer to the geometry of an object's surface in 3D, or to the geometry of a region's bounding contour in 2D. Shape feature extraction and representation are the bases of object recognition in an image. It plays an important role in many image processing applications including content-based image retrieval. The feature extraction stage produces a representation of the content that is useful for shape matching Tyagi (2017). Different Shape Descriptors are shown in Table. 3.

Mary et al. (2017) used Fourier Descriptor in their paper. Boparai and Chhabra (2015) used Zernike Moment in their paper. Effat and Kumar (2017) used BoundingBox, Area, Perimeter, MinorAxisLength, Eccentricity, Solidity, Orientation, MajorAxisLength, EquivDiameter, and ConvexArea for Shape Descriptor and used it with other descriptors.

Table III: Shape Representation

Moments	Boundary (Jiang & Bunke, 1991) Region (Jiang & Bunke, 1991)
Scale-space Methods	Curvature (Mokhtarian & Suomela, 1998) Intersection (Tyagi, 2017)
One-dimensional Function	Complex Coordinates

	Centroid Distance Function Tangent Angle (D. Zhang, Lu, et al., 2001) Contour Curvature (Mokhtarian & Mackworth, 1992) Area Function Triangle Area Chord Length Function (Torquato & Lu, 1993)
Polygonal approximation	Merging Methods Splitting Methods
Spatial Interrelation Feature	Adaptive Grid Resolution (Chakrabarti, Ortega-Binderberger, Porkaew, Zuo, & Mehrotra, 2000) Bounding Box (Tyagi, 2017) Convex Hull (Mathew, Balas, & Zachariah, 2015) Chain Code (Sun & Wu, 2006) Shape Decomposition (Tuanase-Avuatavului, 2005) ALI-based Representation Beam Angle Statistics Shape Matrix (Muller & Rigoll, 1999) Shock Graphs
Shape Transform Domain	Angular radial Fourier Descriptor (Mary et al., 2017) Harmonic Embedding R-Transform (Wang et al., 2007) Shapelets Descriptor Shape Signature Wavelet Transforms (Davatzikos, Tao, & Dinggang, 2003)

2.2 Feature Selection

Feature Extraction is followed by Feature Selection in CBIR system. Feature Selection is related to the selecting most suitable optimal features in order to differentiate image features to check similarity between feature vectors. Idea is to select most appropriate features with consideration of dimension reduction. So that, better discrimination can be done and dimensionality of the feature vector can be reduced.

Boparai and Chhabra (2015) used Genetic Algorithm (GA) along with Feed Forward Back Propagation Neural Network (FFBP) for feature selection. Fadaei et al. (2017) used Particle Swarm Optimization (PSO) for combining and selecting features for color and texture. Mary et al. (2017) used GA for selecting appropriate features. Chang, Yu, Sun, and Yu (2017) used Information Fusion for combining and selecting features based on Scalable Vocabulary Tree (SVT). Effat and Kumar (2017) used GA along with Neural Network.

2.3 Similarity Computation

A CBIR system calculates visual similarities between a query image and database images using a similarity/distance measure. The output of the retrieval process is not a single image but a list of images which are ranked by their similarity value with the query image (Tyagi, 2017). Similarity is computed using image content descriptors, which combine a feature vector and a similarity measure to express a specific perceptual quality of the image (Faria et al., 2010). The similarity of the images can be calculated by using *Template Matching (TM)* or *Machine Learning (ML)* classification strategies. Image features are matched based on the template matcher classifiers. Different types of Template matching techniques are: (i) Bhattacharya Distance (Dubey, Singh, & Singh, 2015), (ii) Canberra Distance (Vagner, Delamaro, & Nunes, 2017), (iii) Chi-square (Tyagi, 2017), (iv) Earth Mover Distance, (v) Euclidean Distance (Yibing et al., 2017), (vi) Hausdorff Distance (Chang, Yu, et al., 2017), (vii) Histogram Intersection Distance, (viii) Integrated Region Matching, (ix) KullbackLeibler Divergence, (x) Mahalanobis Distance (Tyagi, 2017), (xi) Minkowski-Form Distance (Tyagi, 2017), (xii) Quadratic Form Distance, (xiii) Weighted L1 Distance (Khare & Srivastava, 2017). Euclidean Distance, Minkowski-Form Distance, Weighted L1 Distance, and Chi-square are most famous among all.

Instead of template matching, ML classification techniques can be used. Some of the ML techniques are: (i) Artificial Neural Network, (ii) Support Vector Machine, (iii) Nearest Neighbors, (iv) Clustering Methods, (v) Case-Based Reasoning, (vi) Back Propagation Neural Network, (vii) Naive Byes, and so on.

Lu and Huang (2016) used Nearest Neighbor for texture classification. Mary et al. (2017) used Back Propagation Neural Network (BPNN) along with Genetic Algorithm (GA) for optimizing their retrieval accuracy. Effat and Kumar (2017) used K-Means and Nearest Neighbor in their work.

2.4 Ranking And Relevance Feedback

In CBIR, topmost results are the most important so accurately ranking the conveyed images is of dominant value. CBIR systems rank the images in the result set according to their similarity to the query image. The typical ranking strategy used by many CBIR systems is to fire image content descriptors, so that returned images that are most similar to the query image are placed higher in the rank (Faria et al., 2010). The relevance of an image to the query image is also informed as input (e.g., an image is relevant if it is truly similar to the query image, otherwise it is irrelevant). This information is used as training so that the learning algorithms produce a ranking function that maps similarities to the level of relevance of images to query image. When a new query image is given, the relevance of the returned images is estimated according to the learned function (i.e., this function gives a score to an image indicating its relevance to the query image).

Relevance feedback ensures the relevancy of the retrieved images in order to reduce the intention gap. Relevance feedback has been widely accepted in the field of CBIR as a method to boost the retrieval performance (M. Rui & Cheng, 2009). The typical process for relevance feedback of CBIR is as follows (M. Rui & Cheng, 2009): (1) A CBIR system provides an initial retrieval result. (2) A user provides feedback on some images to sort out the relevant ones and irrelevant ones by human high-level concepts. (3) A machine learns from the feedback, returns a group of new retrieval results back to the user, and goes back to Step 2 until the stop criterion is met or the pre-defined number of iterations is reached. (4) The new results from such a CBIR system based on the relevance feedback should be improved over the previous results.

2.5 Performance Evaluation

The most common methods used to evaluate the performance of CBIR are precision, recall, precision-recall graphs, and graphical representations. The Table IV shows the Confusion Matrix by using it, precision and recall can be achieved.

Table IV: Confusion Matrix

	Predicted Class		
Actual Class		Class = True (T)	Class = False (F)
	Class = True (T)	True Positive (TP)	False Negative (FN)
	Class = False (F)	False Positive (FP)	True Negative (TN)

$$Precision\ (P) = \frac{TP}{TP + FP} \tag{1}$$

$$Recall\ (R) = \frac{TP}{TP + FN} \tag{2}$$

$$F\text{-}Score = 2 * \left(\frac{P * R}{P + R}\right) \tag{3}$$

The value of Precision and Recall lies between 0.0 and 1.0. Other Performance Measures are Average Precision, Average Recall, and Average Normalized Modified Retrieval Rank(ANMRR).

2.6 Comparative Study of Different CBIR Techniques

Literature regarding Color, Texture, and Shape descriptors along with different techniques of Feature Combination, Feature Selection, Feature Reduction, Distance Measure, and used datasets for implementations of the research work should be surveyed to gather knowledge about existing CBIR systems. So, better comparison can be made to accomplish research work. In this particular subsection, comparison of the some of the recent techniques used for CBIR is surveyed as shown in Comparative Study:

Table V: Comparative Study of Different CBIR Techniques

Ref.	PP	Feature Extraction			FC\FS \Classifier	DM	Datasets Used
		Color	Texture	Shape			
Fadaei et al. (2017)	HSV	DCD	Wavelet + Curvelet	-	PSO	-	Corel-1k, Corel-10k, Caltech-256, Corel-1k-scale, Corel-1k-illumination
Khare and Srivastava (2017)	Grayscale	-	MS-LBP + GLCM	-	-	Weighted L1	Corel-1k, Olivia-2688, Corel-5k, Corel-10k, GHIM-10k
Mary et al. (2017)	-	Color Moments	GLCM	Fourier Descriptors	BPNN,GA +FSA	ED	Corel-1k
K. L. Rao et al. (2016)	Grayscale	RGB Color Histogram	LMeQEP	-	-	-	Corel-1k, MIT VisTex
T. G. S. Kumar and Nagarajan (2018)	Grayscale	-	LCP + Histogram	-	-	-	Corel-1k, Corel-10k, Brodatz
A. K. Tiwari et al. (2017)	Grayscale	-	Local Descriptors (LBP, LDP, LTP, LTrp, etc.) + Histogram Refinement	-	-	-	GHIM 10000, COREL 10k, Brodatz
Manjunath et al. (2001)	CIELUV	DCD (With GLA)	-	-	-	-	Corel (2500 Images)
M. Rui and Cheng (2009)	HSV	DCD (With Graph Theoretic Clustering)	-	-	FSVM	-	Corel-5k
Chang, Xiaoyang, et al. (2017)	-	-	SIFT+DAISY	-	Information Fusion	Hausdroff	Oxford Building Dataset, Corel-48, PKU-198

Table V: Comparative Study of Different CBIR Techniques

Ref.	PP	Feature Extraction			FC\FS \Classifier	DM	Datasets Used
		Color	Texture	Shape			
Vipparthi and Nagar (2014)	RGB	-	CDLQP	-	-	L1, L2, Canberra, d1 distance	Corel, MIT dataset, Brodtz texture dataset
Boparai and Chhabra (2015)	HSV	Color Histogram + Color Moments	Wavelet Transform	Zernike Moment	FFBP,GA	-	60 Images(Flowers, Africans, Mountains, Buses, Horses and Food)
T. S. Kumar and Nagarajan (2015)	Grayscale	-	LSP	-	-	-	Brodatz
Yang et al. (2008)	-	DCD (With LBA)	-	-	-	Modification in Distance Measure	Corel
Walia et al. (2014)	-	DCD (With Modified LBA)	-	-	-	MPEG-7 Distance Measure	Wang, Corel-10k
Islam et al. (2008)	-	DCD (With Modified VQ Algorithm)	-	-	-	ED	Corel (5100 Images)
Li and Bao (2010)	HSV	DCD (With Region Growing Algorithm)	-	-	-	-	Flower, animal, car, etc. (URL: http://www.mypcera .com/photo/index.htm)
Talib et al. (2013)	-	WDCD	-	-	-	Quadratic, ED	Corel-1k, Caltech-101 (26 classes), Cartoon-5k
Soni and Mathai (2015)	-	Color Histogram + Color Correlogram	-	-	-	ED	Wang

Table V: Comparative Study of Different CBIR Techniques

Ref.	PP	Feature Extraction			FC\FS \Classifier	DM	Datasets Used
		Color	Texture	Shape			
Lu and Huang (2016)	-	-	ILBP	-	Nearest neighbor	G-statistic	RotInv_16_10, Outex
Effat and Kumar (2017)	Median filter, DWT	Color Moments	GLCM	Geometric Property	K-Means, NN,GA	ED	Wang

⟹ **Terms:** PP- Pre-processing, FC- Feature Combination, FS- Feature Selection, DM- Distance Measure.

3. CONCLUSIONS

Performance is not up to mark when Color, Texture, or Shape descriptors individually applied. So it may possible to enhance the performance of CBIR systems by determining the better composition of Color, Texture, and Shape Descriptors. This paper reviews that Feature extraction phase can be improved by using dimensionality reduction methods of machine learning in order to reduce computation complexity. Better selection of the features can be made by using different feature selection methods. To achieve more relevancy, one of the most prominent technique is relevance feedback that is well known from text retrieval. This technique has proven to be important for image retrieval as well because often unexpected or unwanted images show up in the result of a similarity query. The active selection of relevant and irrelevant images by the user represents an interactive method for controlling the pertinence of the results adequately.

Furthermore this fused techniques can improve overall system performance when used with different machine learning classification techniques for ranking images along with different distance measures.

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