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Recent evaluation on Content Based Image Retrieval

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Abstract— Content Based Image Retrieval (CBIR) is the technique of retrieving the similar images from the large database as per user query by matching the contents of images. CBIR is widely used in various computer vision applications such as medical field, E-commerce, Satellite Imaging, and Art Collections and so on. Different types of contents which can be used for retrieving images are Color, Texture, Shape, and/or Spatial Information. The performance of CBIR depends vitally on Feature Extraction, Feature Reduction, Feature Selection, Similarity Measure, Classification, and Ranking. This paper presents the review of different feature extraction strategies used recently for CBIR. Literature review of different Feature Extraction methods used for evaluating the performance CBIR are discussed in order to grasping details about the domain. This review article mainly focuses on the feature extraction which is most crucial part of the CBIR system.

Keywords— CBIR, Feature Extraction, Color, Texture, Shape

I. Introduction

CBIR is the technique of retrieving the similar images based on the contents of the images. Content is nothing but, the dominant or prominent details of the image like Color, Texture, Shape, and/or Spatial information. Retrieving images from large dataset based on the given query is not an easy task. After proliferation of the digital images, it is challenge to find methodology which provides better performance than the existing ones.

Conventional image retrieval techniques are based on the text or metadata of particular image. Which is also known as Text Based Image Retrieval (TBIR). This type of approach is not suitable when we are working with large dataset. Working with large dataset leads us to burden of naming or annotations (which can be manual or automatic). Another issues are related to human perceptivity and deeper need (Liu, et al. 2007). To overcome the above issues in TBIR, CBIR came into the picture in the early 1980s (Chang, et al. 2017). Extracting features from content of the image is not an small task when numerous images are in the dataset. Though many refined methodologies have been proposed to describe color, shape, and texture features till now (Khare 2017). Searching, Managing, and Maintaining the images are made easier by CBIR.

Applications of CBIR are (1) Medical (Antani, Long and Thoma 2008), (2) Crime prevention (Shriram, Priyadarsini and Baskar 2015), (3) Remote Sensing and Geographic Positioning System (Joshi, Purohit and Mukherjee 2017), (4) Art collections, (5) Photograph Archieves (Kadobayashi and Tanaka 2005), (6) Retail Catalogs, (7) Face Recogition (Tan and Triggs 2007), and many more.

Section II contains brief literature survey of feature extraction CBIR system along with building blocks of CBIR. Some of the recent related work done in the area of CBIR is also explained in that section. Section III contains deduded conclusion of this review paper.

II. Literature Survey

CBIR systems can be divided mainly between Feature Extraction, Feature Selection, Similarity Computations (Distance Measures), and Ranking of the images. Feature Extraction is related to the reducing the dimensionality and using details or contents of the images which may possibly provide better discrimination between feature of images. Feature Extraction is the core part of the CBIR system.

Building blocks of the CBIR system are as per shown in the Figure 1.

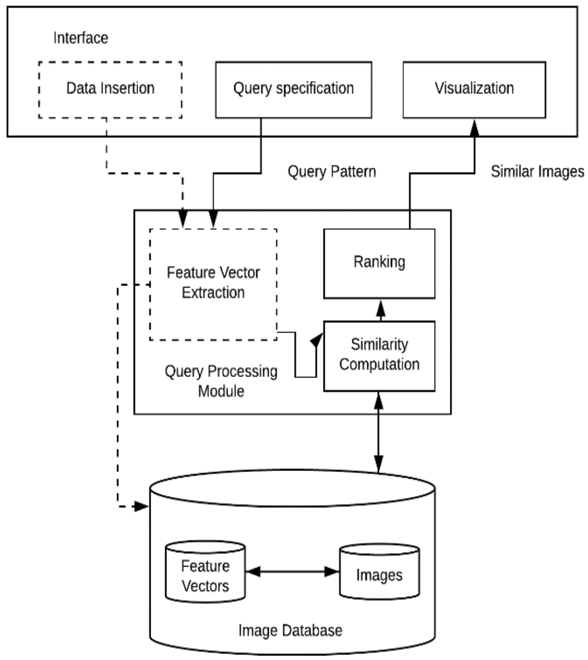

Figure 1: Block Diagram of CBIR system (Tyagi 2017)

As per shown in the figure, the generated query from the user is given to the query processing module along with some data. This query and all the dataset images are used to evaluate features which is used latter for matching of the features. Extracting features is related to finding the details like Color, Texture, Shape, and Spatial Information from the image. There are bunch of techniques are available for feature extraction. After then, Extracted features are reduced by using dimension reduction techniques and appropriate features are selected in order to further comparison (Tyagi 2017).
The query features are compared with dataset features by using Similarity Computation methods. Based on the minimum distance, the dataset images are ranked.

Features can be extracted by using *Color, Texture, Shape,* and/or *Spatial Information* as per requirement of the application and user. Color, Texture, and/ or Shape features are not sufficient for getting all the details of the image. So, mostly different feature descriptors are used together for enhancing the performance of the CBIR. The Figure 2 shows the different types of the Color Descriptor. Color Histogram is the most conventional feature descriptor. It can be applied *locally* or *globally* on the image. Whereas, Color Moments provides small feature vector size.

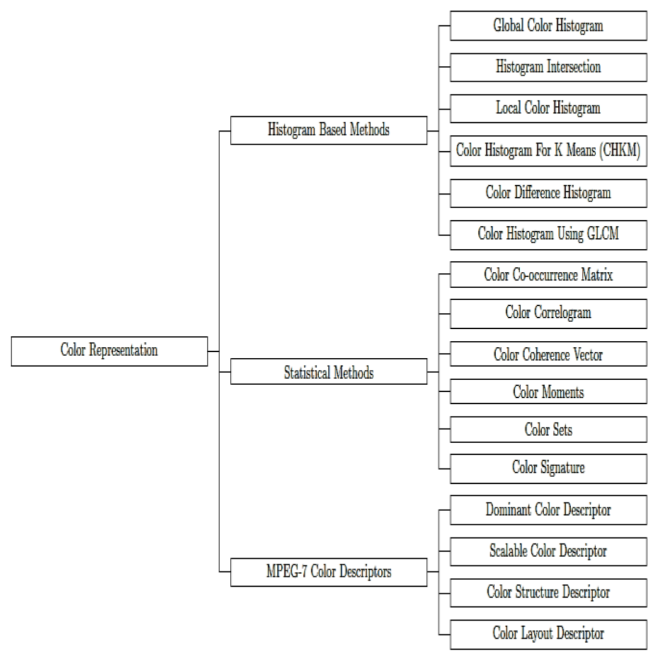

Figure 2: Different Color Descriptors

The Color representation can be classified in three main categories: (1) Histogram Based, (2) Statistical methods, and (3) MPEG-7 Descriptors.

Color Correlogram, Color Coherence Vector (CCV), Color Co-occurrence Matrix are some of the Statistical based approaches. MPEG-7 standard contains different color descriptors like Dominant Color Descriptor (DCD), Color Structure Descriptor (CSD), and Color Layout Descriptor (CLD).

The Texture Representation of different descriptor is shown in Figure 3. Texture Representation can be done based four methods: (1) Perceptual model, (2) Transform model, (3) Statistical model, (4) Structural modal.

Tamura features are example of perceptual modelling. Gabor and Wavelet can be categorized in Transform model. Gray Level Co-occurrence Matrix (GLCM), Local Binary Patterns (LBP), Scale Invariant Feature Transform (SIFT), and so on.

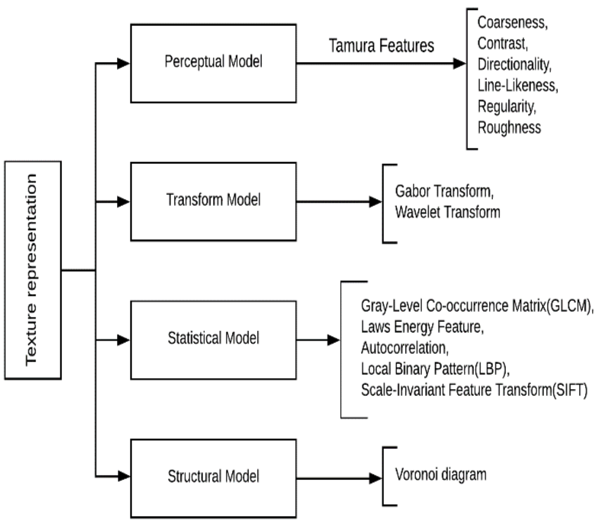

Figure 3: Different Texture Descriptors

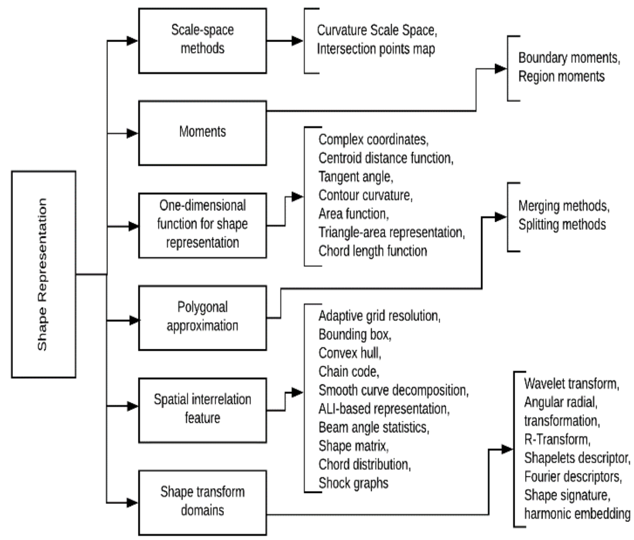

Figure 4: Different Shape Descriptors

The Figure 4 shows Shape descriptors which can be used for CBIR. Shape representation of different techniques is shown below. Shape Descriptors mainly classified in: (1) Scale Space methods, (2) Moments, (3) One Dimensional Functions, (4) Polygonal Approximation, (5) Spatial Interrelation feature, (6) Shape Transform Domains.

The survey of the some of the recent literature is as per discussed below:

T. G. Subash Kumar and V. Nagarajan (Nagarajan and Kumar 2018) proposed texture based descriptor Local Curve Patterns (LCP) for CBIR. Conventional local patterns fail to capture the smoothness over the edges/lines. LCP uses image line/curve characteristics for getting the local patterns. The LCP captures the distinctive spatial relationships in a local region beyond the neighbors by traversing over the direction of curves/ lines in an image. The proposed method was evaluated on Corel-1k, Corel-10k, and Brodatz. This method outshines than some other existing approches like Local Tetra Patterns (LTrp), BOF-LBP, and DBWP.

Wengang Zhou, Houqiang Li, Jian Sun and Qi Tian (Zhou, et al. 2018) proposed Scale Invariant Feature Transform (SIFT) and Convolution Neural Network (CNN) based feature extraction in this paper. Authors introduced Collaborative indexing matrices for CNN and SIFT features. The SIFT and CNN features are firstly evaluated and then, independent index matrix is generated for both techniques. The experimentation was done on the UKBench dataset and the Holidays dataset. The paper mainly focuses on the use of collaborative index embedding in the CBIR.

Prashant Srivastava and Ashish Khare (Khare and Srivastava 2017) proposed texture descriptor, Multi-Scale Local Binary Patterns (MS-LBP) for enhancing the performance of the CBIR. Instead of considering consecutive neighborhood pixels, Local Binary Pattern (LBP) of different combinations of eight neighborhood pixels is computed at multiple scales. Authors introduced different Spatial Patterns than existing Multi-Scale approaches. They applied Gray Level Co-occurrence Matrix (GLCM) over the features of the MS-LBP. This proposed methodology was experimented on five benchmark datasets namely, Corel-1k, Olivia-2688, Corel-5K, Corel-10K, and Ghim-10k.

Sadegh Fadaei, Rassoul Amirfattahi, and Mohammad Reza Ahmadzadeh (Fadaei, Amirfattahi and Ahmadzadeh 2017) proposed optimized integrated approach using Dominant Color Descriptor (DCD), Curvelet, and Wavelet features for CBIR. The authors firstly, calculated DCD, Curvelet, and Wavelet features and then, similarity measure is applied on each of the descriptors in order to combine it with Particle Swarm Optimization (PSO). In this paper, PSO was used for feature combination. The testing was done on Corel-1k, Corel-10k, Caltech-256, Corel-1k-scale and Corel-1k-illumination benchmark datasets. This new DCD based approach outshines than some of the existing literature as shown in the paper.

Naaz Effat and Arun T Kumar (Kumar and Effat 2017) proposed machine learning technique for CBIR. In this paper, They firstly used Descrete Wavelet Transform (DWT) for preprocessing of the dataset images and then, authors applied different descriptors. They used Color Moments as Color descriptor and GLCM as Texture descriptor along with Geometric Shape properties. Features were selected by using

Genetic Algorithm (GA) and for Classification K-means clustering and Neural Network (NN) were used. The experimental results were evaluated on Wang dataset.

Che Chang, X Yu, X Sun, and B Yu (Chang, et al. 2017) proposed DAISY and SIFT for feature extraction to evaluate the enhanced performance of CBIR. Authors firstly, calculated SIFT and DAISY descriptors and secondly, they applied heirarchical clustering along with visual words in order to get histogram representation of the image and in the last similarity is calculated. This paper is mainly focused on the Information Fusion by using Scalable Vocabulary Tree (SVT) with Hausdorff distance measure. They tested this method on datasets namely Corel-9, Corel-48, and PKU-198.

Ashwani Kumar Tiwari, Vivek Kanhangad, and Ram Bilas Pachori (Tiwari, Kanhangad and Pachori 2017) proposed Histogram refinement for texture based descriptors of CBIR. 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. Local patterns corresponding to two sets of pixels are used to generate two histogram features for each image, effectively. The experimentation was done on Corel-10k, Ghim-10k, and Brodatz dataset.

L. Koteswara Rao, D. Venkata Rao, and L. Pratap Reddy (Rao, Rao and Reddy 2016) proposed Local Mesh Quantized Extrema Patterns (LMQeP) for CBIR. In this paper, authors created a mesh structure from a quantized extrema to derive significant textural information. Then, RGB color histogram descriptor was integrated with LMQeP for improving results. Evaluations were taken with respect to Corel-1k and MIT-VisTex benchmark datasets.

The Comparative Survey of some of the recent approaches is shown in the Table 1. FS stands for Feature Selection, FC for Feature Combination, and DM for Distance Measure.

Table 1: Literature survey of state of art methods

Ref.	Feature Extraction	FS\FC	Classifier	DM	Used Datasets
(Nagarajan and Kumar 2018)	LCP	-	-	-	Corel-1k, Corel-10k, and Brodatz
(Zhou, et al. 2018)	SIFT+CNN	-	-	-	UKBench, Holidays
(Khare and Srivastava 2017)	MS-LBP+GLCM		-	Weighted L1	Corel-1k, Olivia-2688, Corel-5K, Corel-10K, and Ghim-10k
(Fadaei, Amirfattahi and Ahmadzadeh 2017)	DCD+Wavelet+Curvelet	PSO	-	-	Corel-1k, Corel-10k, Caltech-256, Corel-1k-scale, Corel-1k-illumination
(Kumar and Effat 2017)	Color Moments+GLCM+Geometric Properies	GA	K-Means+NN	-	Wang
(Chang, et al. 2017)	DAISY+SIFT	SVT		Hausdorff	Corel-9, Corel-48, and PKU-198
(Tiwari, Kanhangad and Pachori 2017)	Texture Patterns (LBP,LTP,LTrp, etc.)+Histogram Refinement	-	-	-	Corel-10k, Ghim-10k, Brodatz

(Rao, Rao and Reddy 2016)	LMQeP+RGB Color Histogram	-	-	-	Corel-1k, MIT-VisTex

III. CONCLUSION

CBIR is still not getting the desirable amount of performance and so much amount of literature is available for this research area. Large bunches of techniques are available out there but, no single technique provides maximum evaluated results. Every Technique has its own pros and cons. It's fully depend on user that which methodology they should use.

Thus, it's clear that no single technique provides all type of features. So, it may possible to improve the performance of the CBIR by using combinations of different techniques. Furthermore, Machine Learning (ML) and Deep Learning (DL) features can improve the performance.

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