Towards Comprehensive Understanding of Image Retrieval Approaches

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Abstract: A key goal of recent researches on image retrieval is to develop retrieval systems that respond to individual user's query for real time applications. Such a speculative development in this field can be attained through more effective approaches with reduced computational complexity and increased/enhanced retrieval accuracy. This paper reports on the recent trends in Content Based Image Retrieval approaches and their resolved issues. The approaches available in the literature to retrieve images from database can be meaningfully categorized into non-iterative approaches and iterative approaches. A thorough analysis is conducted on these approaches and a detailed comparison based on their positive effects, negative effects and retrieval results have been presented.

Key words: Content Based Image Retrieval · Query · Relevance Feedback · Precision · Recall Rate

INTRODUCTION

With the exponential growth of image databases in internet, there is a need to store and retrieve the image data for analysis. Traditionally, two types of approaches are available to perform image retrieval task: (i) Annotation Based Image Retrieval (ABIR) and (ii) Content Based Image Retrieval (CBIR) as shown in figure 1. Annotation based retrieval system manually annotate the images by text descriptors to retrieve the user's query. The main drawback of ABIR is the labor in manual annotation. CBIR utilizes computer vision techniques to search a query image in large image databases. Images of user interest are retrieved by comparing the visual low level features of a query image such as color, texture and shape with features from image database based on the feature's similarity measure. Hence, feature extraction is the salient step involved in CBIR system and its efficiency depends upon the techniques used to derive the features from images. Various techniques have been proposed in literature to extract the simple low level features automatically and to retrieve images from large databases using these features. But low level descriptors have limitations in dealing with large scale databases and cannot describe the semantic features like human perception. Such low level descriptors make the CBIR system inefficient, which is the key problem with this system.
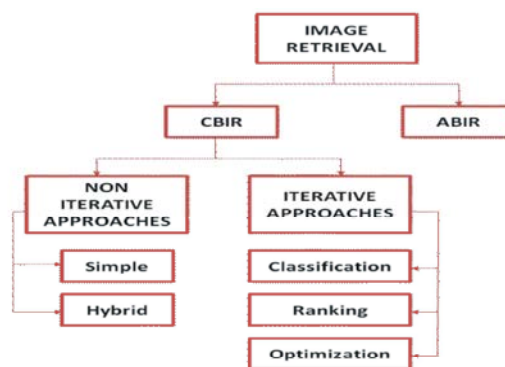

Fig. 1: Proposed Taxonomy of Image Retrieval

Several researchers seek to combine low level features with high level features to reduce the semantic gap which in turn often increases the feature dimension, computation time and retrieval complexity. These complexities require a huge need for improvement in semantic performance of CBIR system. As depicted in figure 1, the approaches proposed in literature to retrieve images from database can be classified into two, namely: i) Non-iterative approaches and ii) Iterative approaches. The main contribution of this paper is as follows:

- To present and analyze the recent methodologies available in Non-Iterative and Iterative approaches.
- To compare the performance of these approaches.
- To provide future research directions.

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The organization of this paper is described in a nutshell as follows: Section 2 describes the techniques proposed in Non-iterative methodologies over past decade. Section 3 presents a deep analysis on Iterative approaches. Section 4 compares the performance of these approaches and provides useful discussion on their results. Section 5 concludes the study [1-10].

Non-Iterative Approaches: The approaches developed to retrieve images in traditional CBIR system is termed as Non-iterative approaches. A traditional CBIR system represents visual information of an image in database as a multi-dimensional feature vector using feature extraction techniques. Query image from the user also undergoes similar feature extraction steps like database images. The extracted features are compared with feature set in the data base and the images that closely resemble the query image are ranked according to the similarity score for displaying the ranked images to the user. Relevant images that are most similar to the query are shown to the user. Non-iterative schemes presented in the literature can be broadly classified into simple and hybrid feature extraction methodologies.

Simple Feature Extraction Methodologies: Various techniques have been proposed in literature to extract the simple automatically and to retrieve images from large databases using these features. Simple features describe an image content using any one of the low level features namely color, texture and shape features. In retrieval, the similarity between the simple feature vector of a query image and the simple feature vectors of the images in the database are compared. Hence, simple feature schemes reduce the computational and time complexity.

Color Feature: Color is the prominent visual feature of an image. A variety of important color features are found in the literature, including color histogram [1], color moments (CM) [2], color coherence vector (CCV) [3], color correlogram [4], dominant color descriptor (DCD), scalable color descriptor (SCD) and color structure descriptor (CSD) [5]. Color features are extracted from an image to describe the color distribution. Lack of considering color distribution in traditional method provides poor adaptability in CBIR systems. To resolve this drawback, adaptive color feature extraction methodology by preserving color distributions up to the third order has been proposed [6]. Adaptive feature extraction methodology utilizes Fixed Cardinality (FC) and Variable Cardinality (VC) for extracting color feature based on image color distribution. The dependency of DCD on the dynamic quantization method makes it more compact and efficient than a global image histogram descriptor.

Positive Effects: Color feature is vulnerable to complicated backgrounds and invariant to image size and different orientations.

Negative Effects: Even though Color histogram are invariant to rotation, translation, do not consider the spatial distribution of the color and can change slowly with occlusions [6-20].

Texture Feature: Color feature becomes inefficient for similar color images in database. This leads to difficulty in the retrieval process. But, texture features retrieve the image or image parts with reference to the changes in certain directions and the scale of the images. Local Binary Pattern is one of the block-based texture features used in CBIR. Center-symmetric local binary pattern (CS-LBP) is a modified version of LBP which combines LBP with scale invariant feature transform (SIFT) [16] for texture description. Two types of local edge patterns (LEP) histograms, namely LEPSEG and LEPINV for image segmentation and image retrieval respectively have been proposed [17]. Robust local patterns (RLP) [18] is created by weighting the center pixel subsequently by scaling factors and constructing two efficient patterns namely Sign Local Binary Pattern (S_LBP) and Magnitude Local Binary Pattern (M_LBP). The histogram of RLPs and a combination of the Gabor transform with the RLPs for different weighting factors are concatenated to form the feature vector. A texture pattern that evaluates the relationship among the surrounding neighbors for a given center pixel in an image has also been proposed in literature for biomedical image retrieval [19]. In the local tetra pattern (LTrP) [20], the encoding is based on direction using horizontal and vertical derivatives that lead to better retrieval accuracy when compared with LBP, local ternary pattern and the LDP on grayscale images. This makes local tetra pattern suitable for other pattern recognition applications such as face recognition, fingerprint recognition, etc.

Positive Effects: Texture features are invariant to rotation, scaling and translation.

Negative Effects: The demerit of the texture feature is that it is applicable only to images with salient texture.

Shape Feature: Many image based applications rely on binary images like trademark, patent images, technical drawings, medical images. Images from such applications/ database usually contain no color and minimum texture information. Hence shape is the useful information to be extracted from such databases. The shape may be defined as a surface configuration of an object. It allows an object to be distinguished from its surroundings by its outline. Classically available techniques are Fourier Descriptors, MPEG7 edge histogram descriptor (EHD) [21], SIFT [22], histogram of gradients (HOG). Shape representations can be generally categorized into two:

- Boundary-based shape representation only uses boundary of the object and can be obtained by describing the specific region using its external characteristics; i.e., the pixels along the object boundary.
- Region-based shape representation uses the entire shape region and can be obtained by describing the considered region using its internal characteristics; i.e., the pixels contained in that region.

A shape descriptor with characteristics like affine invariant, robustness, low computational complexity, compactness is referred as a good shape descriptor. Shape features are invariant to illumination changes, but these complicated features cannot outperform simple histograms.

Hybrid Feature Extraction Methodologies: Hybrid feature extraction methodologies utilize multiple features to form new features and contain valuable information than simple features. The poor retrieval accuracy in retrieval systems using simple features leads to the development of hybrid feature extraction methodologies. Hybrid features include various combinations like Color fused texture feature, Color fused Shape feature, Color fused saliency feature.

Color Fused Texture Feature: As user takes the photograph at different view point and illumination conditions, a single best representation of an image is not suitable for all perceptual subjectivity. Hence, hybrid features become a solution to these issues. Although semantic gap is very difficult to eliminate, researchers strive hard to reduce the gap by fusing color and texture features. Color histogram along with the texture feature based on the co-occurrence matrix constitutes the feature vector. Hence fusing these two features provides a better visual feeling than previously available methods in literature [23]. Usually, color-texture extraction methods use individual color spaces like RGB, HSV, etc. But local oppugnant color space extrema pattern (LOCSEP) [24] converts the image in RGB color spaces into HSV color spaces. The joint color-directional local edge pattern (DLEP) features extracted from the oppugnant color space of RV, GV and BV constitutes oppugnant DLEP features. To tackle the problem of time and computational complexity, an effective method based on region codes to minimize computation time has been proposed [25-40]. Region codes are derived from ROI overlapping block and a method to find the similarity while considering the relative locations of multiple ROIs is also proposed. Finally, effective combination of dominant color and texture features is utilized for ROI image retrieval which results in user satisfaction and less computational time.

Color Fused Shape Feature: In early approaches, histogram technique which represents the frequency of occurrence of pixels is used to describe the color feature. The inefficiency of classical histogram in determining perceptual uniform color difference makes color difference histogram (CDH) [25] more powerful in retrieving processes. CDH seems to be a general solution to the problem of lack in considering perceptual difference between any two colors in L*a*b color space. Analysis of the color image can be performed well by achieving good retrieval rates than those of MPEG-7 edge color layout descriptor (CLD) and the multi text on histogram (MTH) [26] using CDH. It can represent the uniform color difference between colors and edge orientations perceptually and take spatial information in the L*a*b* color space into consideration.

Image feature description resembling human visual perception is an open challenge in CBIR. An image feature descriptor called hybrid information descriptors (HIDs) has been derived using mutual information descriptors (MIDs) and the self information descriptors (SIDs) for image retrieval which is further integrated with Cross-Media retrieval to implement the image retrieval efficiently [15]. MIDs which conform to the human optical nerve system derive the internal correlation between color and shape feature spaces. SIDs extract the feature based on the resolution i.e.) color structure from high resolution image and shape structure from low resolution image. HIDs involve 3 scale resolution images for feature extraction. MIDs are extracted from the original resolution image and SIDs are obtained from the multi-resolution images. After fusing these features, the images are retrieved based on the similarity. This method shows better retrieval efficiency at the cost of computational complexity.

Color Fused Saliency Feature: The performance of DC can be improved by saliency feature which has been widely utilized in many computer vision algorithms. The salient points are unique points of the object in any image. Several methods [7-11] have been proposed to derive saliency map from images. To enhance the performance of DCD, two salient object detection algorithms are utilized: one for natural images and another simple one for cartoon images because the latter type of images is characterized by the object of cartoons surrounded by bold dark contours [12, 13]. This salient algorithm is integrated with the weighted dominant color descriptor, which assumes weight to each dominant color according its spatial location, whether it belongs to the salient object or the background (border). Thus, the semantic performance of the DCD is be improved by integrating saliency with weighted DCD [14].

Iterative Approaches: Iterative approaches refer to the CBIR methodologies with Relevance Feedback (RF) which is one of the most useful tools to improve the retrieval accuracy of a CBIR. In RF step, user provides manual label as either semantically relevant or irrelevant samples (positive or negative feedbacks). Formally, relevance feedback is the process of incorporating user's relevance judgments on the retrieved images returned initially by CBIR systems. RF will approach the user's query images by automatically altering a query from a user based on the relevance judgment governed by previously retrieved results. The refinement of the retrieval results can be made by learning the query images from the feedback perspective. Basically, the process of image retrieval with relevance feedback has four steps:

- Displaying number of retrieved images to the user;
- User explanation about relevant and non-relevant images;
- Learning the user intention through his/her feedbacks; and (iv) Selecting a new set of images to display.

These steps are iterated until a satisfactory result is reached. Hence these sort of approaches are termed as iterative approaches. Relevance feedback technique can be classified into three categories based on the way of dealing with the user submitted a query and the user provided positive examples.

- Classification Approaches
- Ranking Approaches
- Optimization Approaches

Classification approaches consider the problem of retrieving relevant images as a classification [39], [40]]. Ranking approaches merges multiple queries into single one and views the retrieval problem as a ranking problem [31].

Classification Approaches: Even the origin of relevance feedback is from text retrieval, the performance of the CBIR system can also be enhanced by ranking the query results. This implies that relevance feedback is a supervised learning technique which relies on the interactions between the user and the search engine through labeling of the relevance judgment as either positive feedback or negative feedback.

Batch Mode Active Learning: An efficient framework for relevance feedback batch mode active learning which manually labels by considering a number of informative examples through a number of iterations has been proposed [28]. One of the surprising features of batch mode active learning is that reduction in redundancy in the number of available informative examples by providing unique information for model updating. Early relevance feedback depends on two well known methods namely, the query point movement and re-weighting method. The query point movement method may move the ideal query point towards positive samples rather than negative ones to upgrade the estimation of it. Reweighting method tends to change weight for each image feature element. But the assumption in all these methods is that the target class has elliptical shape which leads to poor performance.

Support Vector Machine Classification: Several RF methodologies have been proposed for the positive and negative feedbacks during the last few years. Analyzing the machine learning algorithm, support vector machine (SVM) provides an idea of One-class support vector machine which can estimate the density of positive feedbacks but leaves the negative feedbacks [29] whereas two-class that SVM evaluates positive and negative feedbacks from each other but treats the two groups equally. One of the main drawbacks of regular SVM is its applicability only for binary classification. Hence it may not suit for multiclass problem. To tackle this, the SVM ensemble technique was proposed and has shown better improvement over the regular SVMs. A new SVM approach based on ensemble multiple classifiers has been proposed [30]. This technique begins with the selection of the useful informative images using active feedback learning to label which is followed by boundary learning.

Boundary learning simply allows constructing the boundary which separate the images that satisfy a user's query concept and left images in the dataset. Sub feature vectors are used to train the set of one class SVM classifiers. Using the parameters for positive and negative samples, the weight vectors are evaluated dynamically and the results of the component classifiers are combined to form an output code which increases the retrieval accuracy.

Geometric Optimum Experimental Design: An active learning method, namely geometric optimum experimental design (GOED), which simultaneously selects more informative samples in the database from the unlabeled samples is utilized to assist the user in labeling. This scheme is energized by the regularization principle in the literature [34], [35] which significantly improves the retrieval performance. However GOED differs from regularization approaches by effectively choosing the informative samples and involves three stages: first, a data-dependent kernel for labeled and unlabeled samples is learned, then GOED is utilized to select representative samples of the unlabeled collections and finally, this kernel function along with GOED is used to choose more informative samples to avoid insufficient and inexact label feedback.

Non-Dominated Sorting Genetic Algorithm: One of the interesting issues in CBIR systems with relevance feedback method is that it should maintain high precision accuracy even at first iteration and the space for undiscovered regions should be explored. Achieving both these issues seems to be a difficult task in CBIR system. A hybrid approach which uses a scattered algorithm with other existing techniques at different stages has been proposed [37]. Particularly, scattered algorithm based on non-dominated sorting genetic Algorithm

(NSGA II) used only in the first iteration of the relevance feedback process can be viewed as an optimization problem. From the second iteration onwards a classical based distance measure is used. Thus, this hybrid approach reduces the conflicts between discovering new regions of interest and obtaining acceptable levels of precision at the first.

Ranking Approaches

Navigation-Pattern-based Relevance Feedback: More specifically relevant feedback is not amenable for real time online image retrieval on a large scale database like the web. As depicted in the figure 2, the query from user1 and user2 is that to retrieve "seashore" and "horse" images respectively. Using relevance feedback for this query must provide two different results for the users depending on their concept as shown in fig.2. This is a serious semantic problem in CBIR systems which may result in poor performance and can also be viewed as exploration convergence. Even, weighted K-Nearest Neighbor has not succeeded in differentiating the concept of "seashore", "horse", "seashore and horse". To overcome the problem of exploration convergence and redundant browsing, Navigation-Pattern-based Relevance Feedback (NPRF) has been proposed. The general aim of this technique is to attain high precision effectively and efficiently. By merging three query refinement strategies, including Query Point Movement (QPM), Query Reweighting. Hence NPRF is an optimal way which integrates navigation pattern with the three RF strategies to achieve good exploration of images [31].

Biased Discriminant Analysis: Biased Discriminant Analysis (BDA) is also used as an image retrieval technique with relevance feedback. But the singularity problem of the positive within-class scatter matrix due to the minimum number of positive samples than the feature
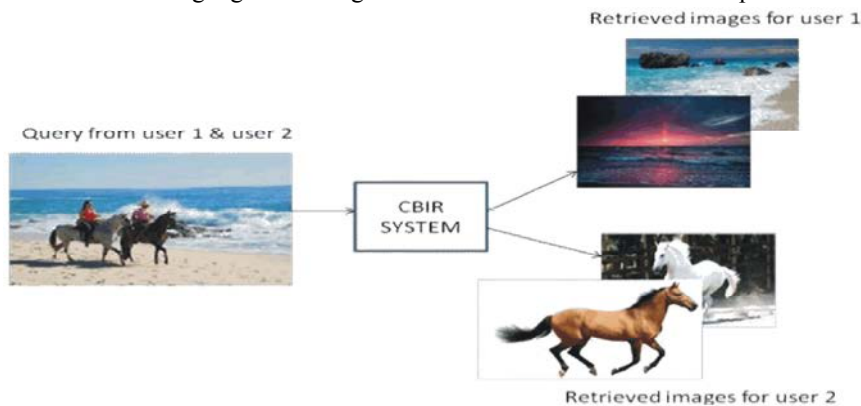

Fig. 2: Example for semantic retrieval systems

dimensionality affects the performance of BDA. The blind assumption of single Gaussian distribution for all the samples is not genuine for real time applications. To avoid these intrinsic problems, an algorithm called generalized BDA (GBDA) for CBIR has been proposed which tackles the singular problem by utilizing the Differential Scatter Discriminant Criterion (DSDC) and manages the Gaussian distribution assumption by redesigning the between-class scatter with a nearest neighbor approach [33].

Manifold Ranking Approaches: Graph based ranking models are most widely used in information retrieval. A famous graph based ranking model known as manifold ranking, ranks the data samples according to the intrinsic data structure of the large number of data. Manifold ranking shows excellent performance on various types of data like text, image and video. Manifold ranking (MR) will consider the ranking score assigned for each data sample as a similarity measure instead of traditional similarity measures. MR was firstly applied to CBIR for capturing the semantic relevance degree which increases the retrieval performance in [50]. But MR is not applicable for large scale databases where graph construction and ranking puts computation overhead. On real time scenario, the query will always be out of sample which makes the framework more complex to handle an out-of-sample query. This difficulty arises as it is acceptable to re-compute the model for new query. The original manifold ranking is extended to resolve the issues in traditional Manifold ranking such as scalable graph construction and efficient computation for out of sample retrieval. Initially, an anchor graph is constructed on the database rather than traditional k-nearest neighbor graph. The ranking computation is speeded up by constructing adjacency matrix. Thus Extended MR (EMR) can handle a database with 1 million images and do the online retrieval in notable time.

A new technique for CBIR with relevance feedback inspired by the random walker algorithm for image segmentation which is closely related to Manifold Ranking Based Image Retrieval (MRBIR) and Multiple Random Walk (MRW) has been proposed [32]. MRBIR and MRW transform the CBIR problem with relevance feedback into a graph-theoretic problem, where nodes and graph edge weights represent images and image similarities respectively. ''Seed'' nodes of the random walker problem are assigned by the relevant and non-relevant images labeled by the user at every feedback. The probability that a random walker starting from that image will reach a relevant seed before encountering a non-relevant one along the graph represents the ranking score. It also possesses various positive features as

parameter-free, provided that image similarity is given, easy to implement and scalable to large dataset.

Multi-Query Parallel Field Ranking: More complex ranking approaches discussed [41-50] in literature are inspired by the fact that naturally occurring images can be created by organized system. These ranking approaches allow the CBIR system have few degrees of freedom than the usual approaches [47, 48]. Commonly manifold ranking approaches employ affinity graph to evaluate the data manifold and Lapalcian regularizer is constructed over the graph to smooth the ranking function along the dataset. Thus manifold-based approaches tend to increase the retrieval performance. The main key issue with manifold based approach is that the ranking function should preserve the ranking order of the data points. To resolve this issue, Multi-Query Parallel Field Ranking (MQPFR) has been proposed which accomplishes highest ranking score for multiple queries through learning an optimal ranking function on the data manifold. This technique roots from vector field theories and builds multi-query information into a single objective function. The gradient field of the ranking function is made as parallel as possible, to point the queries in their neighborhoods. This ranking function varies linearly along the geodesics of the data manifold and achieves the highest ranking score at the multiple queries simultaneously [49].

Optimization Approaches: One method to improve the performance of the CBIR system with RF is to view it as an optimization problem, i.e.) introducing a stochastic component in the process that leads to computationally efficient RF approaches. Hence finding similar image that most likely matches the query image resembles minimizing a valid fitness function. Consider the migration of swarm particles on a multidimensional feature space populated by the database images. Each image in the database is represented by visual attention feature vector and the fitness function is minimized such that the particle approach images which are similar to the user's query. PSO-RF method is based on feature reweighting and swarm updating. Feature reweighting specifies feature weights for two classified image subset that allows the system to understand vital features for discriminating between relevant and irrelevant images. In parallel, the swarm is updated at a constant rate for converging it to the image cluster having best fit found across iterations [38].

Positive Effects: RF regulates the search process by formulating the search operation into iterative steps for approaching the target/relevant image.

Negative Effects: RF acts as a conceptual screen that hides the computational complexity. The difficulty with this approach is that it needs more human intervention for training data completely, which is infeasible for real-world systems.

PERFORMANCE COMPARISON AND DISCUSSIONS

A comprehensive survey on recent methodologies proposed in CBIR field is presented; the next task is to compare some of the important technologies available in the recent past for efficient retrieval of images from database. Percentage precision and recall are used to measure the performance of any proposed system with other competing methods. Let $ç_r$ be the set of relevant images in the database and $ç_t$ is the set of top retrieved images for a query image. The percentage precision and percentage recall for a query image are given as,

$$\Pr ecision = \frac{\eta_t \cap \eta_r}{\eta_t} \times 100\% \qquad (1)$$

$$\mathrm{Re} call = \frac{\eta_t \cap \eta_r}{\eta_r} \times 100\% \qquad (2)$$

The following abbreviations are used in the Table I: 'P' is Precision, 'MAP' is Mean Average Precision, RR is Recall Rate and ARR is average Recall Rate. Table I shows the performance comparison of some of the Non-iterative and Iterative approaches proposed in CBIR field. From the comparison we can state that hybrid feature descriptor supersedes simple low level features. Compared to non-iterative approaches, iterative approaches produce better retrieval accuracy at the cost of computational complexity. Hence, semantic gap in CBIR systems can be reduced using iterative approaches.

Table 1: Performance comparison of existing solutions

Existing Solutions	Dataset Used	Measures			
		P	MAP	RR	ARR
ACFH [6]	Corel Corp	83	-	-	-
	Datacraft Crop	80	-	-	-
CDH	Corel 5k	57.3	-	68.7	-
[25]	Corel10k	45.24	-	54.3	-
HID[15]	Corel1k	79.67	-	95.6	-
	Oliva	52.67	-	19.4	-
	New Caltech	45.93	-	30.8	-
	Corel10k	49.15	-	59	-
WDCD	Corel1k	-	38.0	-	-
[14]	Caltech 26	-	29.8	-	-
	Cartoon5k	-	16.6	-	-
RLP[18]	Corel	75.7	-	-	-
	Brodatz	-	-	-	76.19
DLEP	Corel5k	48.8	21.1	-	-
[17]	Corel10k	40.0	15.7	-	-
LMP	OASIS MRI	56.34	-	-	-
[19]	NEMA CT	98	-	-	-
	VIA/I-ELCAP	89	-	-	55
LOCSEP [24]	Corel1k	99.6	-	-	77.6
	MIT Vis Tex	-	-	-	99
LTrP [20]	Corel1k	75.9	-	-	48.93
	Brodatz	-	-	-	85.3
	MIT Vis Tex	-	-	-	90.16
Color + Texture [23]	Car Dataset	80.9	-	-	-
User navigation Pattern [31]	Corel	96	-	-	-
Random Walks [32]	Oliva	95	-	-	-
SVM based active feedback [30]	Corel	-	-	67	-
GBDA [33]	Corel	30.73	-	-	-
GOED [28]	Corel	-	-	75	-
PSO-RF[38]	CalTech256	-	-	82	-
	Corel	-	-	80	-
SBMMA [36]	Real world				
	Image Database	-	-	81	-
	Corel	-	91.6	-	-
MQPFR [49]	Corel	57	-	41.9	-
	CMU PIE	78	-	86.9	-

CONCLUSION

The primary contribution of this review article include: i) in-depth analysis of iterative and non-iterative approaches proposed in this decade and ii) comparison of these approaches and research directions. This explorations clearly suggests that non-iterative approaches are well suited for real time applications with reduced computational cost, where as iterative approaches achieves user satisfaction at high computational cost with reduced semantic gap. For these reasons, research and development on retrieval systems are still in progress to provide the balance between complexity and satisfaction.

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