Comparative Evaluation of Image Retrieval Algorithms using Relevance Feedback and it's Applications

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ABSTRACT
Now adays, content-based image retrieval (CBIR) is the mainstay of image retrieval systems. To be more profitable, Relevance Feedback (RF) techniques were incorporated into CBIR such that more precise results can be obtained by taking user's feedbacks into account. In this paper Content Based Image Retrieval algorithms using Relevance Feedback technique are discussed. The comparative study of these algorithms is done. This article covers various techniques for implementing Content Based Image Retrieval algorithms , their evaluation parameters used and various possible applications of Content Based Image Retrieval algorithms .

Keywords
Content-based image retrieval, relevance feedback, precision, convergence

1. INTRODUCTION
Multimedia contents are growing explosively and the need for multimedia retrieval is occurring more and more frequently in our daily life. Due to the complexity of multimedia contents, image understanding is a difficult but interesting issue in this field. [14] The relevance feedback techniques were incorporated into content-based image retrieval algorithms during the early and mid-1990s. Since then, this topic has attracted tremendous attention in the CBIR community – a variety of solutions has been proposed within a short period, and it remains an active research topic today. The reasons are that more ambiguities arise when interpreting images than words, which makes user interaction more of a necessity; and in addition, judging a document takes time, while an image reveals its content almost instantly to a human observer, which makes the feedback process faster and more sensible for the end user.[18] Number of powerful image retrieval algorithms have been proposed to deal with the problems over the past few years.

The rest of the paper is organized as follows: Image Retrieval and Relevance Feedback are discussed briefly in section 2. Section 3 provides a brief about the RF based Content Based Image Retrieval algorithms. The comparison of these methods is tabulated in section 4. Section 5 describes the various possible practical applications of CBIR. In section 6 the challenges to the researchers working in CBIR field are discussed. Section 7 concludes the paper.

2. IMAGE RETRIEVAL AND RELEVANCE FEEDBACK
Content-based retrieval is characterized by the ability of the system to retrieve *relevant* images based on the visual and semantic contents of images.[2] Content-based image retrieval, uses the visual contents of an image such as *color*, *shape*, *texture*, and *spatial layout* to represent and index the image. CBIR is the application of computer vision techniques to the image retrieval problem, that is, the problem of searching for digital images in large databases. The CBIR system works as follows: The visual contents of the images in the database are extracted and described by multi-dimensional feature vectors. The feature vectors of the images in the database form a feature database. To retrieve images, users provide the retrieval system with example images or sketched figures. The system then changes these examples into its internal representation of feature vectors. The similarities /distances between the feature vectors of the query example or sketch and those of the images in the database are then calculated and retrieval is performed with the aid of an indexing scheme. The indexing scheme provides an efficient way to search for the image database.[3]
Relevance Feedback (RF) is the process of automatically adjusting an existing query using the information fed back by the user about the relevance of previously retrieved objects such that the adjusted query. The key issue in relevance feedback is how to effectively utilize the feedback information to improve the retrieval performance. [19] After obtaining the retrieval results, user provide the feedback as to whether the results are relevant or non relevant. If the results are non-relevant the feedback loop is repeated many times until the user is satisfied.

3. CONTENT BASED IMAGE RETRIEVAL ALGORITHMS USING RELEVANCE FEEDBACK
Pengyu Hong, Qi Tian, Thomas S. Huang (2000) [5] have proposed an approach to utilize both positive and negative feedbacks for image retrieval. Support Vector Machines (SVM) was applied to classify the positive and negative images. The SVM learning results were used to update the preference weights for the relevant images. This approach releases the user from manually providing preference weight for each positive example.
Xiang Sean Zhou Thomas S. Huang (2001) [6] proposed the on-line learning algorithms for content-based multimedia information retrieval which focused on the

similarity metric issue named as Kernel based biased discriminant analysis (KBDA).

Su, Zhang, Li, and Ma (2003) [7] have given an approach to relevance feedback based CBIR using a Bayesian classifier. Positive examples in the feedback were used to estimate a gaussian distribution that represents the desired images for a given query.

Steven C. H. Hoi, Michael R. Lyu and Rong Jin (2005) [8] have proposed a novel technique to integrate the log information of user feedback into relevance feedback for image retrieval.The algorithm's construction was based on a coupled support vector machine which learns consistently with the two types of information: the low-level image content and the user feedback log.

Wei Jiang, Guihua Er, Qionghai Dai, Jinwei Gu (2005)[9] have incorporated long-term relevance feedback (LRF) with HA to increase both efficiency and retrieval accuracy of CBIR systems. The work contains two parts. (1) Through LRF, a multi-layer semantic representation was built to automatically extract hidden semantic concepts underlying images. HA with these concepts alleviates the burden of manual annotation and avoids the ambiguity problem of keyword-based annotation. (2) For each learned concept, semi-supervised learning was incorporated to automatically select a small number of candidate images for annotators to annotate, which improves efficiency of HA.

Mohammed Lamine Kherfi and Djemel Ziou (2006) [10] presented a new RF framework based on a feature selection algorithm that combined the advantages of a probabilistic formulation with those of using both the positive example(PE) and the negative example (NE). Through interaction with the user, the algorithm learns the importance of image features, and had applied the results obtained to define similarity measures that correspond better to the judgement. The use of the NE allows images undesired by the user to be discarded, thereby improving retrieval accuracy.

Anelia Grigorova et al.(2007)[11] have suggested a new concept semantically based feature space modification called feature adaptive relevance feedback (FA-RF). FA-RF is a RF-based approach that have used two iterative techniques to exploit the relevance information: query refinement and feature re-weighting.

Wei Bian and Dacheng Tao (2010)[12] have represented images by low-level visual features. They have designed a mapping to select the effective subspace from for separating positive samples from negative samples based on a number of observations. They have proposed the Biased Discriminative Euclidean Embedding (BDEE) which parameterizes samples in the original high-dimensional ambient space to discover the intrinsic coordinate of image low-level visual features.

Yu Sun, Bir Bhanu (2010) [13] suggested a new content based image retrieval (CBIR) system combined with relevance feedback and the online feature selection procedures. A measure of inconsistency from relevance feedback was explicitly used as a new semantic criterion to guide the feature selection. By integrating the user feedback information, the feature selection was able to bridge the gap between low-level visual features and high-level semantic information, leading to the improved image retrieval accuracy.

Ja-Hwung Su et al.(2011)[14] have proposed a novel method, Navigation-Pattern-Based Relevance Feedback (NPRF), to achieve the high efficiency and effectiveness of CBIR. In terms of effectiveness, the proposed search algorithm NPRF Search makes use of the discovered navigation patterns and three kinds of query refinement strategies, Query Point Movement (QPM), Query Reweighting (QR), and Query Expansion (QEX).

Manish Chowdhury , Sudeb Das, and Malay Kumar Kundu (2012) [15] have presented content based image retrieval (CBIR) system based on a new Multiscale Analysis (MGA)-tool, called Ripplet Transform Type-I (RT).To improve the retrieval result, a fuzzy relevance feedback mechanism (F-RFM) was implemented. Fuzzy entropy based feature evaluation mechanism was used for automatic computation of revised feature's importance and similarity distance at the end of each iteration.

The standard parameters which are used for the experimental evaluation of the results by the above stated algorithms are precision, recall and accuracy.

Precision is defined as number of retrieved relevant images divided by total number of retrieved images and the recall is number of retrieved relevant images divided by total number of relevant images in the database. [11] The Standard Deviation serves as an error-bar, while the precision is the major evaluation method.[12] The criterion precision delivers the ability for hunting the desired images in user's mind and the coverage represents the ability for finding the accumulated positive images in a query session.[14] Accuracy can be calculated as relevant images retrieved in top T returns divided by T. [7] The formulas for calculation of these evaluation parameters can be given as following:

$$\text{Precision} = \frac{\text{Number of retrieved relevant images}}{\text{Total number of retrieved images}}$$

$$\text{Recall} = \frac{\text{Number of retrieved relevant image}}{\text{Total number of relevant images in the database.}}$$

$$\text{Accuracy} = \frac{\text{Relevant images retrieved in top T returns}}{\text{T}}$$

4. COMPARISON OF CBIR ALGORITHMS USING RF TECHNIQUES

The following table provides the comparison of various Content Based Image Retrieval algorithms using Relevance Feedback techniques.

S.NO.	AUTHOR	YEAR	PROPOSED METHOD	DATASET USED	EVALUATION PARAMETER	PERFORMANCE RESULTS
1	Pengyu Hong, Qi Tian, Thomas S. Huang	2000	Support Vector Machine with Relevance feedback	Corel Image Gallery	Feature Vectors: Color Moments Wavelet Moments	Number of hits in top 20 returned images = 18
2	Xiang Sean Zhou Thomas S. Huang	2001	Kernel Based Biased Discriminant Analysis (KBDA)	Corel Image Gallery	Mean and Variance	Mean =17.0 Variance = 8.86
3	Su, Zhang, Li, and Ma	2003	Bayesian classifier	Corel Image Gallery	Accuracy	Accuracy increase in top 10 results = 13.4 % in top 20 results =7.8% and in top 100 results =2.6 %
4	Steven C. H. Hoi, Michael R. Lyu , Rong Jin	2005	Log Based Relevance Feedback By Coupled Support Vector Machine(LRF-CSVM)	Corel Image Gallery	Precision	Mean Average Precision= 0.471
5	Wei Jiang, Guihua Er, Qionghai Dai, Jinwei Gu	2005	Hidden Annotation(HA) with Long Term Relevance Feedback Learning(LRF)	Corel Image Gallery	Precision	Average Precision= 0.75
6	Mohammed Lamine Kherfi and Djemel Ziou	2006	Probabilistic feature weighting using positive example (PE) and negative example (NE)	Calphotos collection from Pennsylvania State University	Precision	Average Precision= 0.8
7	Anelia Grigorova, et al.	2007	Feature Adaptive Relevance Feedback(FA-RF)	UC Berkeley digital library project	Precision and Recall	Precision=0.6406 Recall=0.6833
8	Wei Bian and Dacheng Tao	2010	Biased Discriminative Euclidean embedding (BDEE)	Corel Image Gallery	Precision. And standard deviation	Average Precision = 0.32 for 9 RF iterations
9	*Yu Sun, Bir Bhanu*	2010	Relevance Feedback with online Feature selection	1. Butterfly Image Database 2.Google Images	Precision	For Dataset 1 Precision=0.8 For Dataset 2 Precision=0.75
10	Ja-Hwung Su et. al	2011	Navigation-Pattern-Based Relevance Feedback(NPRF)	Corel image database and the Web images	Precision	Average precision=0.910
11	Manish Chowdhury, Sudeb Das, and Malay Kumar Kundu	2012	Ripplet Transform (RT) and Fuzzy Relevance Feedback Mechanism (F-RFM)	SIMPLIcity Database	Precision	Average precision=0.80

5. APPLICATIONS OF CBIR

a. Crime prevention

Law enforcement agencies typically maintain large archives of visual evidence, including past suspects, facial photographs, fingerprints, tyre treads and shoeprints. Whenever a serious crime is committed, they can compare evidence from the scene of the crime for its similarity to records in their archives.

b .The military

Military applications of imaging technology are probably the best-developed, though least publicized. Recognition of enemy aircraft from radar screens, identification of targets from satellite photographs, and provision of guidance systems for cruise missiles are known examples. Many of the surveillance techniques used in crime prevention could also be relevant to the military field.

c. Intellectual property

Trademark image registration, where a new candidate mark is compared with existing marks to ensure that there is no risk of confusion, has long been recognized as a prime application area for CBIR. Copyright protection is also a potentially important application area. Enforcing image copyright when electronic versions of the images can easily be transmitted over the Internet in a variety of formats is an increasingly difficult task. There is a growing need for copyright owners to be able to seek out and identify unauthorised copies of images, particularly if they have been altered in some way.

d. Architectural and engineering design

Architectural and engineering design share a number of common features – the use of stylized 2- and 3-D models to represent design objects, the need to visualize designs for the benefit of non-technical clients, and the need to work within externally-imposed constraints, often financial. Such constraints mean that the designer needs to be aware of previous designs, particularly if these can be adapted to the problem at hand. Hence the ability to search design archives for previous examples which are in some way similar, or meet specified suitability criteria, can be valuable.

e. Fashion and interior design

Similarities can also be observed in the design process in other fields, including fashion and interior design. Here again, the designer has to work within externally-imposed constraints, such as choice of materials. The ability to search a collection of fabrics to find a particular combination of colour or texture is increasingly being recognized as a useful aid to the design process

f. Journalism and advertising

Both newspapers and stock shot agencies maintain archives of still photographs to illustrate articles or advertising copy. These archives can often be extremely large (running into millions of images), and dauntingly expensive to maintain if detailed keyword indexing is provided. Broadcasting corporations are faced with an even bigger problem, having to deal with millions of hours of archive video footage, which are almost impossible to annotate without some degree of automatic assistance.

g. Medical diagnosis

The increasing reliance of modern medicine on diagnostic techniques such as radiology, histopathology, and computerized tomography has resulted in an explosion in the number and importance of medical images now stored by most hospitals. While the prime requirement for medical imaging systems is to be able to display images relating to a named patient, there is increasing interest in the use of CBIR techniques to aid diagnosis by identifying similar past cases.

h. Geographical information systems (GIS) and remote sensing

Although not strictly a case of *image* retrieval, managers responsible for planning marketing and distribution in large corporations need to be able to search by spatial attribute (e.g. to find the 10 retail outlets closest to a given warehouse). And the military are not the only group interested in analysing satellite images. Agriculturalists and physical geographers use such images extensively, both in research and for more practical purposes, such as identifying areas where crops are diseased or lacking in nutrients – or alerting governments to farmers growing crops on land they have been paid to leave lying fallow.

i. Cultural heritage

Museums and art galleries deal in inherently visual objects. The ability to identify objects sharing some aspect of visual similarity can be useful both to researchers trying to trace historical influences, and to art lovers looking for further examples of paintings or sculptures appealing to their taste.

j. Education and training

It is often difficult to identify good teaching material to illustrate key points in a lecture or self-study module. The availability of searchable collections of video clips providing examples of avalanches for a lecture on mountain safety, or traffic congestion for a course on urban planning, could reduce preparation time and lead to improved teaching quality.

k. Home entertainment

Much home entertainment is image or video-based, including holiday snapshots, home videos and scenes from favourite TV programmes or films. This is one of the few areas where a mass market for CBIR technology could develop. Possible applications could include management of family photo albums.

l. Web searching

Cutting across many of the above application areas is the need for effective location of both text and images on the Web, which has developed over the last five years into an indispensable source of both information and entertainment. Text-based search engines have grown rapidly in usage as the Web has expanded; the well-publicized difficulty of locating images on the Web indicates that there is a clear need for image search tools of similar power. Paradoxically, there is also a need for software to *prevent* access to images which are deemed pornographic.

6. CHALLENGES IN RF BASED CBIR SYSTEMS

Research can be done in the area of CBIR to improve the values of evaluation parameter's like precision, convergence, execution time using Relevance Feedback. Researchers can design a CBIR algorithm for different applications like crime prevention, the military ,intellectual property, architectural and engineering design ,fashion and interior design, journalism and advertising, medical diagnosis ,geographical information and remote sensing systems ,cultural heritage, education and training, home entertainment, web searching etc. The retrieval performance of CBIR algorithm using Relevance Feedback technique can be improved for the images having same semantic category. Researchers working in the area of CBIR dealing with very large data sets the relevance feedback techniques can be improved by incorporating with parallel and distributed computing techniques.

7. CONCLUSION

Relevance Feedback is a powerful Technique in CBIR for Multimedia retrieval. In this paper the evaluation of Content Based Image Retrieval algorithms using Relevance Feedback techniques for last ten years, their dataset used and their results are discussed in detail. From the results of the various methods discussed, it can be concluded that to improve the retrieval performance of the CBIR algorithm researchers must have to design the techniques to increase the values of the standard evaluation parameters like precision, convergence ratio or accuracy. The Relevance Feedback technique can be incorporated in CBIR algorithm to obtain the higher values of the standard evaluation parameters used for evaluation of the CBIR algorithm for claiming better results of retrieval performance.

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