A Techniques for CBIR System Based on Image Annotations and Multimodal feature Set

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***Abstract*— Content based Image/Video Retrieval system is a querying system that uses content as a key for the retrieval process. It is a difficult task to design an automatic retrieval system because real world images usually contain very complex objects and color information. In this paper, we discuss some of the key contributions in the current decade related to image retrieval and automated image annotation. We also discuss some of the key challenges involved in the adaptation of existing image retrieval techniques to build useful systems that can handle real-world data. so nowadays the content based image retrieval are becoming a source of exact and fast retrieval. In this paper the techniques of content based image retrieval are discussed, analyzed and compared. It also introduced the feature like visual descriptor and ontology methods. The suggestion for feature methodology's to over come the difficulties and improve the result performance. In this paper we provide an overview of approaches to CBIR. Major approaches to improving retrieval effectiveness via relevance feedback in text retrieval systems are discussed**

***Index Terms*: Inference mechanisms, multimedia databases, Content based image retrieval, Visual descriptor. ontology**.

I. Introduction

It is the application of computer vision techniques to the image retrieval problem (i.e.) the problem of searching for digital images in large databases. An image retrieval system is a computer system for browsing, searching and retrieving images from a large database of digital images. Color, Shape and texture are important cue in extracting information from images; these histograms are widely used in content based image retrieval [13]. Color and texture contain important information but, for instance, two images with similar color histograms can represent very different things. Therefore the use of shape-describing features is essential in an efficient content-based image retrieval system. Although shape description has been intensively researched, there exists no direct answer as to which kind of shape features should be incorporated into such a system [14]. Most traditional and common methods of image retrieval utilize some method of adding metadata such as captioning, keywords or descriptions to the images so that retrieval can be performed over the annotation words.

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Image retrieval has been a very active research area since the 1970s, with the thrust from two major research communities, database management and computer vision. These two research communities study image retrieval from different angles, one being text-based and the other visual-based [15]. The fundamental difference between content-based and text-based retrieval systems is that the human interaction is an indispensable part of the latter system. Humans tend to use high-level features such as keywords, text descriptors, to interpret images and measure their similarity. While the features automatically extracted using computer vision techniques are mostly low-level features [16]. Early techniques of image retrieval were based on the manual textual annotation of images, a cumbersome and also often a subjective task. Texts alone are not sufficient because of the fact that interpretation of what we see is hard to characterize by them. Hence, contents in an image, color, shape, and texture, started gaining prominence [17]. The large amount of manual effort required in developing the annotations, the differences in interpretation of image contents, and inconsistency of the keyword assignments among different indexers. As the size of image repositories increases, the keyword annotation approach becomes infeasible. To overcome the difficulties an alternative mechanism, Content Based Image Retrieval is used [18].

Biomedical images are frequently used in publications to illustrate the medical concepts or to highlight special cases. Conventional approaches for biomedical journal article retrieval have been text-based with little attention devoted to the use of images in the articles. Text-based retrieval uses text information automatically extracted from title, abstract, figure captions, and discussions (mention). It provides fairly good results; however, the relevance quality sometimes is not satisfactory. Content-based image retrieval (CBIR) also has been applied to biomedical image retrieval [19].

Clinicians and medical researchers routinely use online databases such as MEDLINE to search for bibliographic citations that are relevant to a clinical situation. The biomedical evidence they seek is available through clinical decision support systems (CDSS) that use text-based retrieval enhanced with biomedical concepts Clinicians and medical researchers routinely use online databases such as MEDLINE to search for bibliographic citations that are relevant to a clinical situation. The biomedical evidence they seek is available through clinical decision support systems (CDSS) that use text-based retrieval enhanced with biomedical concepts. Authors of biomedical publications frequently use images to illustrate the medical concepts or to highlight special cases. These images often convey essential information and can be very valuable for improved clinical decision support (CDS) and education. The text-based retrieval of the images has, so far, been limited mostly to caption and/or citation information. To be of greater value, images in scientific publications need to be first annotated (preferably, automatically) with respect to their usefulness for CDS to help determine relevance to a clinical query or to queries for special cases important in educational settings [1-3].

This article discusses a method for multimodal image annotation that utilizes (i) image analysis techniques for localization and recognition of author provided overlays on the images; (ii) image feature extraction methods for content-based image retrieval (CBIR); (iii) natural language processing techniques for identifying key terms in the title, abstract, figure caption, and figure citation (mention) in the article; an d (iv) use of structured vocabularies, such as the National Library of Medicine's Unified Medical Language System (UMLS), for identifying the biomedical concepts in the text[3].

As discussed in earlier works [4], these steps can be used to associate the biomedical concepts in the text to specific regions in the image. The relevance to a clinical query is aided by this addition of semantic information to extracted image features for improved CBIR. Traditionally, CBIR tends to be limited to use of visual features in identifying similarity among a collection of images. This has spurred discussion on the "semantic gap" [5] that is introduced when high-level concepts are represented through low-level visual features such as image color, and texture (for example). Such a semantic gap can be minimized through annotation by biomedical concepts that are extracted from the article text and applied to relevant regions within an image.

General content-based image retrieval (CBIR) also could be improved by the proposed approach in a similar manner as text-based retrieval is improved. In this case no text information is available, but only visual features are used. The CBIR identifies relevant articles as text-based retrieval does in the multimodal method. Annotations and ROIs in retrieved images can be identified by the annotation recognizer and then be used to re-rank the results [3].

At present, images needed for instructional purposes or clinical decision support (CDS) appear in specialized databases or in biomedical publications and are not meaningfully retrievable using primarily text-based retrieval systems. Our goal is to automatically annotate images extracted from scientific publications with respect to their usefulness for CDS. A future clinical decision support system (CDSS) could then provide images relevant to a clinical query or to queries for special cases important in educational settings. An important step toward attaining the goal is automatically annotating images and related text. Our approach to automatic image indexing is to describe (or annotate) an image at three levels of granularity:1.coarse, which addresses, a)image modality b).relation to a specific clinical task (image utility),c).body ocation;2.medium,which provides a more detailed description of the image using biomedical domain ontologies;3.spesific,which provides very detailed description of clinical entities and events in an image using terms that are not included in existing ontologies, and often are familiar only to clinicians specializing in a narrow area of medicine[7].

CBIR involves the following four parts in system realization: data collection, build up feature database, search in the database, arrange the order and deal with the results of the retrieval. Fig 1 represents the Block Diagram of CBIR system.

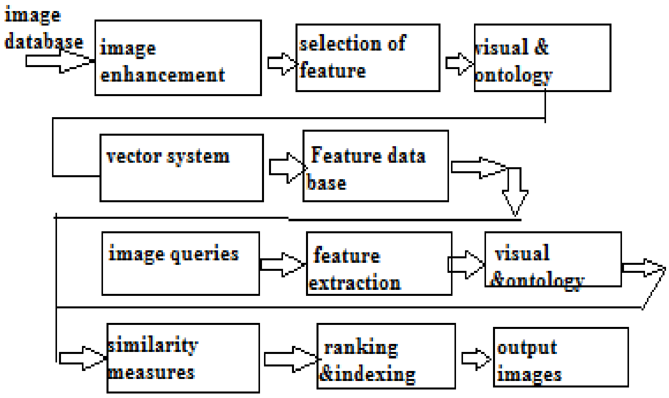

Fig.1. Block Diagram of CBIR system

II. BRIEF SURVEY ON IR SYSTEM

Color feature is the most intuitive and obvious feature of the image, and generally adopt histograms to describe it. Color histograms method has the advantages of speediness, low demand of memory space and not sensitive with the images' changes of the size and rotation, it wins extensive attention consequently. The retrieval based on texture feature is refers to the description of the image's texture, we usually adopt texture's statistic feature and structure feature as well as the features that based on special domain are changed into frequency domain. There is three problems need to be solved during the image retrieval that based on shape feature. Firstly, shape usually related to the specifically object in the image, so shape's semantic feature is stronger than texture. [10]

The retrieval based on annotation is a set of statical models are built based on visual features, manually labeled images to represent to used to propagate keywords to other unlabeled images. The retrieval based on Ontology is a combination of some special ontology visual descriptors to classify the images and find the query views and object views to compare the databases. Search to classify the resultant images is divided in to relevant group and irrelevant group of images.

III. IMPROVING RETRIEVAL EFFECTIVENESS IN IR SYSTEMS

In contrast with the database environment, precise representations for user queries and (text) documents are difficult to generate in an IR environment. Retrieval effectiveness is improved by starting out with an imprecise and incomplete query and iteratively and incrementally improve the query specification [13]. There are two major approaches to improving retrieval effectiveness: automated query expansion, and relevance feedback techniques.

A. *Automated Query Expansion in IR*

Automated query expansion methods are based on term co-occurrences [1], Pseudo-Relevance Feedback (PRF) [1], concept-based retrieval [14], and language analysis [6]. Language analysis based query expansion methods are not discussed in this paper.

B. *Relevance Feedback Techniques in CBIR*

There has been numerous studies on improving retrieval effectiveness in CBIR systems based on relevance feedback (RF) techniques mostly adopted from IR area. In the following we describe salient aspects of some of these approaches. These studies use their own test collections, queries, training data. Therefore, it is rather difficult to provide a comparative assessment of these approaches.

RF techniques assume two-class relevance feedback: relevant and non-relevant classes. For example, Support Vector Machines (SVM) have been used to discriminate between “relevant and “non-relevant images. In the context of CBIR, SVMs first map image signatures (i.e., n-dimensional ectors whose components corresponds to low-level image features) to a higher-dimensional feature space (HDFS) using a non-linear transformation associated to a kernel, and then implicitly perform linear discrimination between “relevant and “non-relevant items in this HDFS. Retrieval user is emulated according to seven significantly different strategies on four ground-truth databases of different complexity. The study concludes that the ranking of the images by these two algorithms don’t significantly depend on the selected strategy. Moreover, the ranking between strategies appears to be independent of the complexity of the ground-truth classes. Peng (2003) propose a multi-class form of relevance feedback retrieval to offset disadvantages of two-class relevance feedback. It is shown that this method is able to create flexible metrics that better capture users’ perceived similarity. The method achieves a higher level of precision with fewer iterations. Fang and Hock (2000) describe a system for CBIR based on multidimensional features associated with color, texture, and shape. They observe that by co-jointly matching image features in a multidimensional space rather than in separate independent feature spaces, the precision in retrieval is improved from 50% to 90% for the top 10 most similar images retrieved. This study has also shown that by including the features corresponding to the image background entails improvement in retrieval precision. The system also employs interactive relevance feedback to improve user query specification and retrieval effectiveness. For each retrieval iteration, the system learns a decision tree to discover commonality among a set of images considered as relevant by the user for a query. The tree is then used as a model for determining which of the unseen images would be of interest to the user. Some researchers use a Bayesian learning algorithm that relies on belief propagation to integrate relevance feedback provided by the user over a retrieval session. This approach entails natural criteria for evaluating local image similarity without the need for image segmentation. They note that region-based queries are considerably less ambiguous than queries based on entire images, and hence entail significant improvements in retrieval precision. Through experimental results, they demonstrate significant improvements in the rate of convergence to the relevant images is possible by the inclusion of learning in the retrieval process.

Relevance feedback approaches to CBIR based on support vector machine (SVM) learning have been shown to significantly improve retrieval performance. These approaches require fixed-length image representations — SVM kernels represent an inner product in a feature space that is a nonlinear transformation of the input space. However, region-based CBIR approaches typically use variable length image representation and define a similarity measure between two variable length representations. Therefore, standard SVM approach cannot be applied to region-based CBIR. This is where generalized SVM (GSVM) comes to the rescue. It allows the use of an arbitrary kernel.Gondra and Heisterkamp (2004) describe an initial investigation into utilizing a GSVM-based relevance feedback learning algorithm, which learns One-class Support Vector Machines (1SVM). Based on experimental results, the study concludes that the learning algorithm improves retrieval effectiveness. They present an improved version of this work that uses an incremental k-means algorithm to cluster 1SVMs in [16]. This version results in scalability and query processing is accelerated by considering only a small number of cluster representatives, rather than the entire set of accumulated 1SVMs.

Zhang and Zhang (2004) study relevance feedback in CBIR as a standard two-class pattern classification problem with the goal of improving retrieval precision by learning through the user relevance feedback data. They have investigated two important unique characteristics of the problem: small sample collection, and asymmetric sample distributions between positive and negative samples. They address this problem by leveraging these two unique characteristics. Different learning strategies are used for positive and negative sample collections. Su, Zhang, Li, and Ma (2003) propose an approach to relevance feedback based CBIR using a Bayesian classifier. Positive examples in the feedback are used to estimate a Gaussian distribution that represents the desired images for a given query. Ranking of retrieved images is determined based on the negative examples

In the relevance feedback. Furthermore, using relevance feedback and Principal Component Analysis (PCA) technique feature subspace is extracted and updated during the feedback process. This entails not only reduction in dimensionality of feature spaces, but also enables obtaining a proper subspace for each feature type to further enhance retrieval effectiveness. Chua, Chu, and Kankanhalli (1999) [11] propose a relevance feedback approach to CBIR by using text and color attributes of images. A pseudo object model based on color coherence vector is used to model color content. The approach uses user relevance feedback to estimate the importance of different attributes. Based on experimental results on a collection of 12,000 images, the study concludes that relevance feedback and pseudo-object based color model are effective in improving retrieval performance. Benitez, Beigi, and Chang (1998) describe Meta Seek, which is a meta search engine to query distributed image collections on the Web. The meta search engine interfaces with four image search engines: Visual Seek, WebSeek, QBIC, and Virage. User feedback is used to evaluate the quality of search results returned by each engine, and this history is preserved in a database. Rui, Huang, and Mehrotra (1998) proposes an approach to CBIR which addresses: the gap between high level concepts and low level image features; and, subjectivity in human perception of image content. Using user's relevance feedback, query term weights are dynamically adjusted to improve retrieval effectiveness. Experimental results on a collection of size 70,000 indicate that the approach significantly reduces user's effort needed in specifying queries.

IV. CONCLUSION:

CBIR systems based on these approaches are expensive to develop and maintain due to extensive human labor, and consistency and subjectivity concerns in indexing and query specification. Advances that led to commercial success in IR area (e.g., Web search engines) present a great potential for such a success in CBIR also. The ubiquitous and intense research interest among CBIR researchers in leveraging lexicons, thesauri, and ontologies to effect concept-based retrieval using relevance feedback is a positive direction in benefiting from the IR advances. However, CBIR evaluation frameworks with elaborate benchmarks — test collections, representative user queries, relevance judgments, system evaluation measures and methods — are essential for making rapid strides in CBIR.

The following three-phased approach seems to hold promise for querying generic (i.e., non domain-specific) image collections by casual users. First, ontology-guided browsing (i.e., retrieval by browsing) is needed to make the user develop a conceptual understanding of the collection and its semantic dimensions. Using this knowledge, in the next phase, the user will specify queries that reflect his information need more closely with minimal effort. The user then engages in incremental query refinement and iterative retrieval by providing relevance feedback with the goal of improving precision. Once the user retrieves a few images of high relevance, he moves on to the third stage, in which he performs retrieval by example using these images. The goal in the third stage is to improve recall by not losing on precision.

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