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Biomedical Image Retrieval Using SVM Classification

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***Abstract* - In the past few years, immense improvement was obtained in the field of content-based image retrieval (CBIR).Nevertheless, existing systems still fail when applied to medical image databases.Simple feature-extraction algorithms that operate on the entire image for characterization of color, texture, or shape cannot be related to the descriptive semantics of medical knowledge that is extracted from images by human experts. In the framework, the probabilistic outputs of a multiclass support vector machine (SVM) classifier as category prediction of query and database images are exploited at first to filter out irrelevant images, thereby reducing the search space for similarity matching. Images are classified at a global level according to their modalities based on different low-level, concept, and key point-based features. It is difficult to find a unique feature to compare images effectively for all types of queries. Hence, a query-specific adaptive linear combination of similarity matching approach is proposed by relying on the image classification and feedback information from users. Based on the prediction of a query image category, individual pre computed weights of different features are adjusted online. The prediction of the classifier may be inaccurate in some cases and a user might have a different semantic interpretation about retrieved images. Hence, the weights are finally determined by considering both precision and rank order information of each individual feature representation by considering top retrieved relevant images as judged by the users. As a result, the system can adapt itself to individual searches to produce query-specific results. Experiment is performed in a diverse collection of many biomedical images of different modalities, body parts, and orientations. It demonstrates the efficiency and effectiveness of the retrieval approach.**

***Keywords* —Classification, classifier combination, content based image retrieval (CBIR), medical imaging, relevance feedback (RF), similarity fusion.**

I. INTRODUCTION

Content-based image retrieval, a technique which uses visual contents to search images from large scale image databases according to users' interests, has been an active and fast advancing research area since the 1990s. During the past decade, remarkable progress has been made in both theoretical research and system development. However, there remain many challenging research problems that continue to attract researchers from multiple disciplines. Before introducing the fundamental theory of content-based retrieval, we will take a brief look at its development. Early work on image retrieval can be traced back to the late 1970s[1]. In 1979, a conference on Database Techniques for Pictorial Applications was held in Florence. Since then, the application potential of image database management techniques has attracted the attention of researchers. Early techniques were not generally based on visual features but on the textual annotation of images. In other words, images were first annotated with text and then searched using a text-based approach from traditional database management systems. Comprehensive surveys of early *text-based image retrieval* methods can be found in previous research. Text-based image retrieval uses traditional database techniques to manage images[2]. Through text descriptions, images can be organized by topical or semantic hierarchies to facilitate easy navigation and browsing based on standard Boolean queries. However, since automatically generating descriptive texts for a wide spectrum of images is not feasible, most text-based image retrieval systems require manual annotation of images. Obviously, annotating images manually is a cumbersome and expensive task for large image databases, and is often subjective, context-sensitive and incomplete.

II. HISTORY

In the early 1990s, as a result of advances in the Internet and new digital image sensor technologies, the volume of digital images produced by scientific, educational, medical, industrial, and other applications available to users increased dramatically[3]. The difficulties faced by text-based retrieval became more and more severe. The efficient management of the rapidly expanding visual information became an urgent problem. This need formed the driving force behind the emergence of content-based image retrieval techniques. In 1992, the National Science Foundation of the United States organized a workshop on visual information management systems to identify new directions in image database management systems. It was widely recognized that a more efficient and intuitive way to represent and index visual information would be based on properties that are inherent in the images themselves[4]. Researchers from the communities of computer vision, database management, human-computer interface, and information retrieval were attracted to this field. Since then, research on content-based image retrieval has developed rapidly. Since 1997, the number of research publications on the techniques of visual information extraction, organization, indexing, user query and interaction, and database management has increased enormously [5].

Similarly, a large number of academic and commercial retrieval systems have been developed by universities, government organizations, companies, and hospitals. Comprehensive surveys of these techniques and systems can be found in previous research [6]. 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. In typical content-based image retrieval systems (Figure 1-1), the visual contents of the images in the database are extracted and described by multi-dimensional feature vectors[7]. 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[8]. Recent retrieval systems have incorporated users' relevance feedback to modify the retrieval process in order to generate perceptually and semantically more meaningful retrieval results [9].

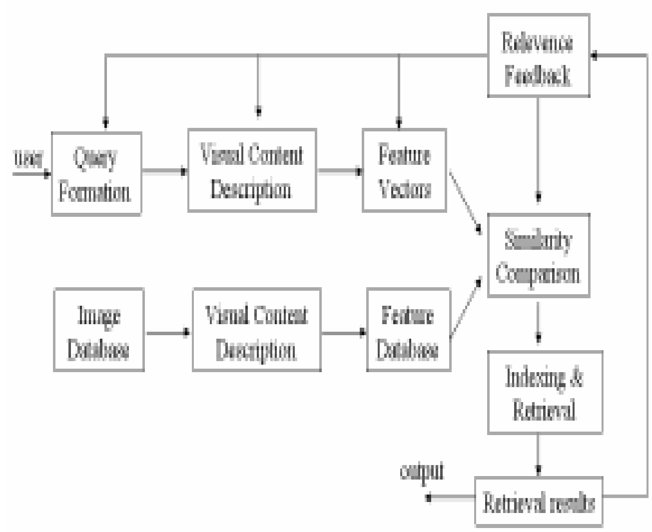

Figure 1-1. Diagram for content-based image retrieval system

III.IMAGE FEATURE REPRESENTATION

The performance of a classification and/or retrieval system depends on the underlying image representation, usually in the form of a feature vector[10]. In a heterogeneous medical image collection, it is possible to identify specific local patches in images that are perceptually and/or semantically distinguishable, such as homogeneous texture patterns in gray level radiological images, differential color, and texture structures in microscopic pathology and dermoscopic images. The variation in the local patches can be effectively modeled as local concepts [11] analogous to the keywords in text documents by using any supervised learning-based classification techniques, such as the SVM [12].

For the SVM training, the initial input to the system is the feature vector set of the patches along with their manually assigned corresponding concept labels. Images in the dataset are annotated with the concept labels by fixed partitioning each image Ij into l regions as {x1j , . . . , xkj , . . . , xlj }, where each xkj ∈ d is a combined color and texture feature vector. For each xkj ,the concept probabilities are determined by the prediction of the multiclass SVMs as [17]

pikj = P(y = i|xkj), 1 ≤ i ≤ L. (1)

Finally, the c ategory label of xkj is determined as cm, which is the label of the category with the maximum probability score. Based on this encoding scheme, an image Ij is represented as a vector of weighted concepts as f concept

j = [w1j , . . . , wij , . . . wLj]T (2)

Where each wij denotes the weight of a concept ci , 1 ≤ i ≤ L in image Ij , depending on its information content. The popular “tf–idf” term-weighting scheme [13] is used in this paper, where the element wij is expressed as the product of local and global weights. In a heterogeneous medical collection with multiple modalities, images are often captured with different views, imaging and lighting conditions, similar to the real world photographic images. Ideally, the representation of such images must be flexible enough to cope with a large variety of visually different instances under the same category or modality, yet keeping the discriminative power between images of different modalities. In this paper, we extract such robust and invariant features from images as "bag of keypoints" [14]. In addition to the previous features, the MPEG-7 [15]-based color layout descriptor (CLD) and edge histogram descriptor (EHD) and descriptors from the lucene image retrieval library [16], such as fuzzy color texture histogram (FCTH) and color edge direction descriptor (CEDD) are extracted to represent images from different perspectives.

IV. SUPPORT VECTOR MACHINES FOR MULTI-CLASS CLASSIFICATION

The Automated classification addresses the general problem of finding an approximation F of an unknown function F defined from an input space [2 onto an u nordered set of classes {wl,... ,wK}, given a training set: T = {(~eP, yP = F(xP)}P1 C ~2 x {•l,...,09K}.

Among the wide variety of methods available in the literature to learn classification problems, some are able to handle many classes (e.g. decision trees [2, 12], feedforward neural networks), while others are specific to 2-class problems, also called dichotomies. This is the case of perceptrons or of support vector machines (SVMs) [1, 4, and 14]. When the former are used to solve K-class classification problems, K classifiers are typically placed in parallel and each one of them is trained to separate one class from the K - 1 others. The same idea can be applied with SVMs [17]. This way of decomposing a general classification problem into dichotomies is known as a one-per-class decomposition, and is independent of the learning method used to train the classifiers. In a one-per-class decomposition scheme, each classifier k trained on the dichotomy {(a:P, yP =/k(a.p))}L 1 c a2 x {-1, +1} produces an approximation fk of fk of the form fk = sgn(gk), where g k : a2 --+ I~. The class wk picked by the global system for an input x will then be the one maximizing gk(a:). This supposes, however, that the outputs of all g k are in the same range.

As long as each of the learning algorithms used to solve the dichotomies outputs probabilities, their answers are comparable [18]. When a dichotomy is learned by a criterion such as the minimization of the mean square error between gk(xP) and yP E {-1, +1}, it is reasonable to expect (if the model learning the dichotomy is sufficiently rich) that for any data drawn with the same distribution than the training data, the output of the classifier will have its module around +1. Thus, in this case again, one can more or less assume that the answers of the wk classifiers are comparable. The output scale of a SVM is determined so that outputs for the support vectors are +1. This scale is not robust, since it depends on just a few points, often including outliers[19]. Therefore, it is generally not safe to decompose a classification problem in dichotomies learned by SVMs whose outputs are compared as such, to provide the final output.

V. SIMILARITY FUSION

It is challenging to find a unique feature representation to compare images accurately for all types of queries. Feature descriptors at different levels of image representation are in diverse forms and may be complementary in nature. In information retrieval (IR), more specifically in text retrieval, data fusion or multiple-evidence combination describes a range of techniques where multiple pieces of information are combined to achieve improvements in retrieval effectiveness [20][21]. Many researchers have argued that better retrieval effectiveness may be gained by exploiting multiple query representations, retrieval algorithms, or feedback techniques and combining the results of a varied set of techniques or representations [21].

A. Category-Specific Similarity Fusion

In this approach, for a query image, its category at a global level is determined by employing the SVM learning. Based on the online category prediction of a query image, precomputed category-specific feature weights (e.g., αF) are utilized in the linear combination of the similarity matching function. Based on this scheme, for example, a color feature will have more weight for microscopic pathology and dermatology images, whereas edge and texture related features will have more weights for the radiographs. The steps involved in this process are depicted in Algorithm 2.

Algorithm Category-Specific Similarity Fusion Approach

(off-line): For a query image Iq,calculate individual Feature vectors fq,where F € {Concept,Keypoint,EHD,CLD,CEDD,FCTH}.

For each feature,get a category prediction based on the probabilistic output of (3) by applying SVM.

Combine the outputs by applying any of the combination rules (e.g.,sum,max,prod,min).

Get the final category label as Wm(q),m € { 1,…….M} of the query image category Wm(q).

Finally,combine the similarity scores with the weights based on similarity fusion in (5).

Finally return the images based on the similarity matching values in descending order to Obtain a final ranked list of images.

B. RF-Based Dynamic Similarity Fusion

A user might have a different interpretation of the semantic description in his/her mind or the prediction of the classifier might go wrong. Hence, it may be advantageous to have the option to interact with the system to refine the search process, such as RF. This section presents a RF-based similarity fusion technique where feature weights are updated at each iteration by considering both the precision and the rank order information of relevant images in the individual result lists based on the feedback from the users. As a result, the final rank-based retrieval is obtained through an adaptive and linear weighted combination of overall similarity fusing individual level similarities.

Algorithm RF-based Similarity Fusion Approach

1. Initially, consider the top K images by applying similarity
Fusion based on an equal feature weighting.
2. Obtain the user's feedback about relevant images from the top K images.
3. Calculate the new query vector Fq^F as the mean vector of the relevant images.
4. For each ranked list based on individual similarity matching.also consider top K
Images and measure the effectiveness as E(f^F).
5. Normalize the effectiveness or weight score to be in the range [0,1].
6. Utilize the normalized scores as updated weights in the similarity function.
7. Continue, step 2 to 6 until no images are noticed.

VI.CONCLUSION

The large number of research publications in the field of content based medical image retrieval especially in recent years shows that it is very active and that it is starting to get more attention. This will hopefully advance the field as new tools and technologies will be developed and performance will increase. The content based image retrieval system clearly shows the advantage of searching images based on similarity fusion and filtering in terms of effectiveness and efficiency. This retrieval framework is useful for large medical databases where a search can be performed in diverse images for teaching, training and research purposes.

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