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Survey on Biomedical Image Retrieval System

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Abstract: With the increasing use of Social media thousands of images are being downloaded & uploaded every day. Content-based image retrieval (CBIR) was in research for the last few years. In particular, there has been growing interest in indexing biomedical images by content. Manual indexing of images for content-based retrieval is cumbersome, error prone, and prohibitively expensive. Due to the lack of effective automated methods, however, biomedical images are typically annotated manually and retrieved using a text keyword-based search. A common drawback of such systems is that the annotations are imprecise with reference to image feature locations, and text is often insufficient in enabling efficient image retrieval. Even such retrieval is impossible for collections of images that have not been annotated or indexed. In the support, the probabilistic outputs of the 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.

Keywords: SVM, CBIR, Feature Extraction.

I. INTRODUCTION

Content-based image retrieval (CBIR) has attracted much research awareness in recent years. In particular, there has been growing interest in indexing biomedical images by content. Manual indexing of images for content-based retrieval is bulky, error prone, and prohibitively expensive. Due to the lack of effective automated methods, however, biomedical images are typically annotated manually and retrieved using a text keyword-based search. A common problem of such systems is that the annotations are imprecise with reference to image feature locations, and text is often insufficient in enabling efficient image retrieval. Even such retrieval is difficult for collections of images that have not been annotated or indexed. Additionally, the retrieval of interesting cases, particularly for medical education or building atlases, is a cumbersome task. CBIR methods developed specifically for biomedical images could offer a solution to such problems, thereby augmenting the clinical, research, and educational aspects of biomedicine[1]. For any class of biomedical images, however, it would be necessary to develop suitable feature representation and correspondence algorithms that capture the "content" in the image. The Lister Hill National Center for Biomedical Communications, a research and development division of the U.S. National Library of Medicine (NLM), maintains a digital collection of 17,000 cervical and lumbar spine images collected in the second National Health and Nutrition Examination Survey (NHANES II) conducted by the National Center for Health Statistics (NCHS) [2, 3, 4, 5]. Classification of the spine x-ray images for the osteoarthritis research community has been a long-standing aim of researchers at the NLM, and collaborators at NCHS and the National Institute of Arthritis and Musculoskeletal and Skin Diseases (NIAMS). Also, the capability to retrieve these images constructed on geometric characteristics of the vertebral structures is of interest to the vertebral morphometry community. Medical experts have identified visual features of the images specifically related to osteoarthritis, but the images have not ever been manually indexed for these features which include anterior osteophytes, disc space narrowing for the cervical plus lumbar spine, subluxation for the cervical spine, and spondylolisthesis for the lumbar spine. Another archive of 100,000 digitized 35mm color slides of the uterine cervix is being created in collaboration with the National Cancer Institute (NCI). Researchers at NCI would like to enable use of these images for research and training at sites around the world. The design of a system to achieve these ends trusts on research in image compression, database management, and CBIR for image query on the uterine cervix images. Automated or computer-assisted classification, query, and retrieval methods for large medical image archives are highly appropriate, since such methods offset the high cost of manual classification and manipulation by medical experts. We are investigating automatic or computer-assisted methods that use image features for indexing and retrieval of these images in a manner acceptable to the biomedical community. In addition, we are devoting research efforts into classification of pathology, such as the detection of occurrence of anterior osteophytes, disc space narrowing, subluxation, and spondylolisthesis in spine images; and squamo-columnar joint boundary, regions with acetowhitening, vasculature, mosaicism and punctation, on the uterine cervix images.

II. LITERATURE SURVEY

A. Related work in CBIR

Content based visual information retrieval definitely has a large potential in the medical domain. The amount of visual data produced in medical departments shows the importance of developing new and alternative access methods to complement text. Content-based methods can be used on a large variety of images and in a wide area of applications. Still, much work needs to be done to produce running applications and not only research prototypes. When looking at most current systems, it becomes clear that few to none of them are actually in routine use. An important factor is to build prototypes that are integrated with a hospital wide communication structure and that use open standards, so data can be exchanged with other applications. It needs to become easy to integrate these new functionalities into other existing applications such as HIS (Hospital Information System)/RIS (Radiology Information System)/PACS or other medical image management or viewing software. In this way, it will become much easier to have prototypes running for a sample of users and to get feedback on the clinical use of systems. To get acceptance, it is important to be integrated into the current applications and with interfaces that the users are familiar with. To win acceptance from the users it is also important to show the performance of the systems and to optimize the performance of systems for certain specialized tasks or people[2]. The gray levels in an image and their distribution or layout throughout the image are often represented with histograms that can be compared with a simple intersection or a Euclidean distance. Local gray-level descriptors can be represented by the most commonly occurring gray level in a certain area or by local gray-level histograms. Textures can be described with wavelet filter responses, which measure the changes in the gray levels in various directions and scales throughout an image, or on the basis of features derived from co-occurrence matrices, which help determine the frequency of occurrence of neighboring gray levels in various directions and distances to describe a texture. These approaches allow description of the texture in terms of scale, principal directions, and whether texture changes are rapid or gradual. Texture descriptors are especially helpful when they are extracted from a region that is homogeneous in texture. Shape features can be used to characterize identifiable or segmented objects and include mathematical moments of the shape as well as features that describe the roundness of the form or the number of changes between convex and concave segments of the contour. Often, the goal is to extract features that are invariant with respect to object size or rotation. By comparing the features of two images, one can calculate a similarity score between the two. Different distance measures for comparisons exist, such as the simple Euclidean or the “city block” distance [34].

A new content-based image retrieval approach for biometric security, which is based on color, texture and shape features and controlled by fuzzy heuristics. The proposed approach is based on the three well-known algorithms: Color histogram, texture and moment invariants. The use of these three algorithms ensures that the proposed image retrieval approach produces results which are highly relevant to the content of an image query, by taking into account the three distinct features of the image and similarity metrics based on Euclidean measure [3]. Color histogram is used to extract the colour features of an image. Gabor filter is used to extract the texture features and the moment invariant is used to extract the shape features of an image. The evaluation of the proposed approach is carried out using the standard precision and recall measures, and the results are compared with the well-known existing approaches. A multi-step approach for content-based image retrieval in medical applications, in general the IRMA concept is related to the Blob world-project [1].

B. Related Work in MedicalDatabase

The first results of using a freely available image retrieval system to achieve content-based access to medical images are very promising. Although no quantitative evaluation has been done as of yet, the first results show that the system already works reasonably well with only a few changes. When using features specially developed for medical images the results promise to get even better. Lung image retrieval of HRCT images will be the first domain that we will specialize our system for. These images exhibit texture features that describe a pathology well and they will be a good test bed for trying several texture descriptors. Another important domain for improvement is the inclusion of not only query functionalities into MRML but also database functionalities. An application like CasImage can then easily manage its entire database for content-based access via MRML on a remote Linux server [8].The focus of many participants in this year’s ImageCLEF has been text–based retrieval. The increasingly semantic topics combined with a database containing high–quality annotations in 2009 may have resulted in less impact of using visual techniques as compared to previous years. Visual runs were rare and generally poor in performance. Mixed–media runs were very similar in performance to textual runs when looking at MAP. The analysis also shows that several runs with very few relevant images have a very low average performance, whereas topics with a larger number seem to perform better.

Case–based topics were introduced for the first time and only a few groups participated with results being slightly lower than for the image–based topics. A kappa analysis between several relevance judgments for the same topics shows that there are differences between judges but that agreement is generally high. A few judges can nevertheless have disagreeing results with all other judges, something that we need to investigate further. For future campaign it seems important that more research on visual techniques including massive learning should be done as currently techniques do not perform well. Interactive and manual retrieval do also seem to have room for improvements and should be put forward to participants who generally prefer automatic text–based approaches[9]. This is a domain where visual image categorization algorithms can have a significant impact as they can quickly classify very large numbers of images, for example from web repositories [12]. MPEG-7, formally known as Multimedia Content Description Interface, includes standardized tools (descriptors, description schemes, and language) enabling structural, detailed descriptions of audio-visual information at different granularity levels (region, image, video segment, collection) and in different areas (content description, management, organization, navigation, and user interaction). It aims at supporting and facilitating a wide range of applications such as media portals, content broadcasting, and ubiquitous multimedia. In this paper, we present a high-level overview of the MPEG-7 standard. First discuss the scope, basic terminology, and potential applications. Next, discuss the constituent components. Then, compare the relationship with other standards to highlight its capabilities [20].

C. Related work in Relevance Feedback

Targeted at a very specific application scenario, namely the real-time learning from user interactions during information retrieval, relevance feedback as a classification or learning problem possesses very unique characteristics and difficulties. A successful algorithm is the one tailored to address these special issues[13].CBIR has emerged as one of the most active research areas in the past few years_ Most of the early research effort focused on finding the best image feature representations Retrieval was performed as summation of similarities of individual feature representation with fixed weights While this computer centric approach establishes the basis of CBIR the usefulness of such systems was limited due to the difficulty in representing high level concepts using low level features and human perception subjectivity. In this paper we introduce a Human Computer Interaction approach to CBIR based on relevance feedback Unlike the computer centric approach_ where the user has to precisely decompose his information need into different feature representations and precisely specify all the weights associated with them the proposed interactive approach allows the user to submit a coarse initial query and continuously refine his information need via relevance feedback This approach greatly reduces the users effort of composing a query and captures the users information need more precisely Furthermore the efficiency and effectiveness of the proposed approach have been validated by a large amount of experiments_ Although the proposed retrieval model is for CBIR it can be easily expanded to handle other media types such as video and audio The proposed model also has a close relationship to MPEG as discussed in our previous MPEG proposal Furthermore the proposed model provides a natural way of combining keyword features with visual features. We envision the importance of supporting keywords with visual features and are currently expanding our system to handle this. One of the future research directions of this approach is to explore optimal or suboptimal weight updating strategies Currently the weight updating strategy is heuristic based and may not be the best solution Techniques such as Expectation Maximization EM are promising techniques worth exploring[14]. Content-based image retrieval (CBIR) framework for varied collection of medical images of different imaging modalities, anatomic regions with different orientations and biological systems is planned. Organization of images in such a database (DB) is well dissimilar with predefined semantic categories; hence, it can be useful for category-specific searching. The proposed framework consists of machine learning methods for image prefiltering, similarity matching by statistical distance measures, and a relevance feedback (RF) scheme. To narrow down the semantic hole and increase the retrieval efficiency, examine both supervised and unsupervised learning techniques to associate low-level global image features (e.g., color, texture, and edge) in the expected PCA-based Eigen space with their high-level semantic and visual categories. Especially, explore the use of a probabilistic multiclass support vector machine (SVM) and fuzzy c-mean (FCM) clustering for categorization and prefiltering of images to decrease the search space. A category-specific statistical similarity matching is planned in a finer level on the prefiltered images. To incorporate improved perception subjectivity, an RF mechanism is also added to update the query parameters dynamically and adjust the proposed matching functions. Experiments are based on a ground-truth DB consisting of 5000 various medical images of 20 predefined categories. Analysis of results base on cross-validation (CV) accurateness and precision-recall for image categorization and retrieval is reported. It demonstrates the enhancement, effectiveness, and efficiency achieved by the proposed framework [6].

D. Related Work in Classification

A novel image retrieval framework based on image categorization, concept feature representation and retrieval is proposed for the diverse medical image collections of different modalities. Unlike few other approaches where image categorization is the very first step of image processing for filtering out irrelevant images, we have taken a different approach. In this framework, the category information is utilized directly to adjust the feature weights in a linear combination of similarity matching. Specially, we explore the utilization of the probabilistic multi-class SVM and various classifier combination rules in different aspects of the image feature spaces for the categorization, representation and similarity matching of the images. Overall, this framework might be useful as a front-end for medical databases where a search can be performed in diverse images for teaching, training and research purposes. In future, we will investigate to incorporate other learning methodologies such as, boosting and relevance feedback (RF) and will integrate the textual modality in the framework [15]. Techniques for improving accuracy of medical image retrieval by representing image content at an intermediate level local visual concept level. The intermediate level is higher than low-level visual features that are traditionally used and a step closer to the high-level semantics in the image content. A visual concept is defined for local image regions and an image may comprise of several concepts. The feature space is enhanced by exploiting the correlations and structural relationships among these visual concepts. Using SVM-based training, the proposed image representation schemes realize semantic abstraction via prior learning when compared to the representations based on the low-level features [16]. A support vector machine (SVM) is a concept in statistics and computer science for a set of related supervised learning methods that analyze data and recognize patterns, used for classification and regression analysis. The standard SVM takes a set of input data and predicts, for each given input, which of two possible classes forms the input, making the SVM a non-probabilistic binary linear classifier. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on [17]. The support vector machine is a supervised classification system that minimizes an upper bound on its expected error. It attempts to find the hyper-plane separating two classes of data that will generalize best to future data . Suppose we are given i training data x1, ..., xi that are vectors in some space X ∈ RN . We are also given their labels y1, ..., yi where yi ∈ {−1, +1}. Assuming that the samples are linearly separable, there are many possible hyper-planes that can separate the samples, but there is only one that maximizes the distance between the hyper-plane and the closest points [24]. Multiclass SVMs are usually implemented by combining several two-class SVMs. The one-versus-all method using winner-takes-all strategy and the one-versus-one method implemented by max-wins voting are popularly used for this purpose. In this paper we give empirical evidence to show that these methods are inferior to another one-versus one method: one that uses Platt's posterior probabilities together with the pairwise coupling idea of Hastie and Tibshirani. The evidence is particularly strong when the training dataset is sparse[23].

E. Related Work in Feature Extraction

Feature extraction is the premise of CBIR. To generalize we can say that, components may incorporate both text-based elements (catchphrases, explanations) and visual elements (color, surface, shape, faces). Since there exists rich writing on content based element extraction in the database administration framework, we will keep ourselves to the strategies of visual component extraction. Inside the visual component scope, the elements can be further classified as general elements and domain specific elements.

One of the important features in texture is Energy level [10]. Texture properties include coarseness, Contrast, Directionality, Line-likeness, Regularity, and roughness which define the image which is characterized by the spatial distribution of gray levels [35]. Here we are using energy level algorithm which is as follows:

1) Step 1: The image is decomposed into four sub-images.\
2) *Step 2:* In this second step the calculation of the energy of the decomposed subbands, which is calculated using:

$$E = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} | X\,(i\,,j)|$$

The dimensions of the image are denoted by M and N. The X denotes the intensity of pixels of the ith row and jth column of the image map.

3) *Step 3:* Repeat Step 1 until the index is 3,The technique makes the energy levels of the sub-bands were calculated and were further decomposed into low-level sub-band[36]. Edge map is regarded as one of the fundamental importance in image processing which has a huge effect on processing; therefore, the edge detection has been given the maximum effort. It produces a kind of ground truth data for the subsequent feature extraction; therefore, a proper edge map detection technique is required [37]. The edge can be defined as a strong intensity contrast or a jump in the intensity of an image within a confined range. The histogram is a representation of the distribution of colors of an image. When it comes to digital images the histogram represents the number of pixels of particular colors. Each list contains a fixed list of the color range which is present over the span of

image color space. The base of the histogram can be any kind of color space of three-dimensional, the color space used can be RGB or HSV[38].

III. CONCLUSION

This paper has surveyed the essential concepts of medical image retrieval systems. This survey attempt to initiate the theory and practical applications of medical image retrieval. Use of the hybrid feature including color, texture and shape as feature vector of the regions to match images can give better results. Classification and content-based retrieval methods based on the features they use such as colour, texture, and shape are discussed along with their subclasses.

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