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Content based Medical Image Retrieval with SVM Classification and Relevance Feedback

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ABSTRACT
As the network and development of multimedia technologies are becoming more popular, users are not satisfied with the traditional information retrieval techniques. So now a day the content based image retrieval using relevance feedback are becoming a source of exact and fast retrieval. The idea of Content-based Image Retrieval (CBIR) using Relevance Feedback systems is to automatically extract image contents based on image features, i.e. color, texture, and shape and store in database and compare input query image feature with the features stored in database. Relevance feedback is applied to reduce the gap between high-level image semantics and low-level image features. Semantic gap is the difference between human perception of a concept and how it can be represented using machine level language.

Keywords: Content-based image retrieval, Relevance feedback, SVM, CLD, EHD

1. INTRODUCTION
An image retrieval system is a computer system for browsing, searching and retrieving images from a large database of digital images. Most of the traditional and common methods of image retrieval use some method of adding metadata such as captioning, keywords, or descriptions to the images so that retrieval can be performed over the annotation words. Manual image annotation is time-consuming, laborious and expensive; to address this, there has been a large amount of research done on automatic image annotation. Additionally, the increase in social web applications and the semantic web have inspired the development of several web-based image annotation tools. Content-based image retrieval (CBIR) has attracted much research interest in recent years [1]. In particular, there has been growing interest in indexing biomedical images by content [2, 3, 4, and 5]. Manual indexing of images for content-based retrieval is cumbersome, error prone, and prohibitively expensive [6]. 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. Additionally, the retrieval of interesting cases, especially 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. For any class of biomedical images, however, it would be necessary to develop suitable feature representation and similarity algorithms that capture the “content” in the image.

2. ARCHITECTURE OF MEDICAL IMAGE RETRIEVAL
Fig. 1 shows the general scheme of image retrieval from a database using relevance feedback. The basic idea of relevance feedback is to reduce the burden of finding the right query formulation from the user.

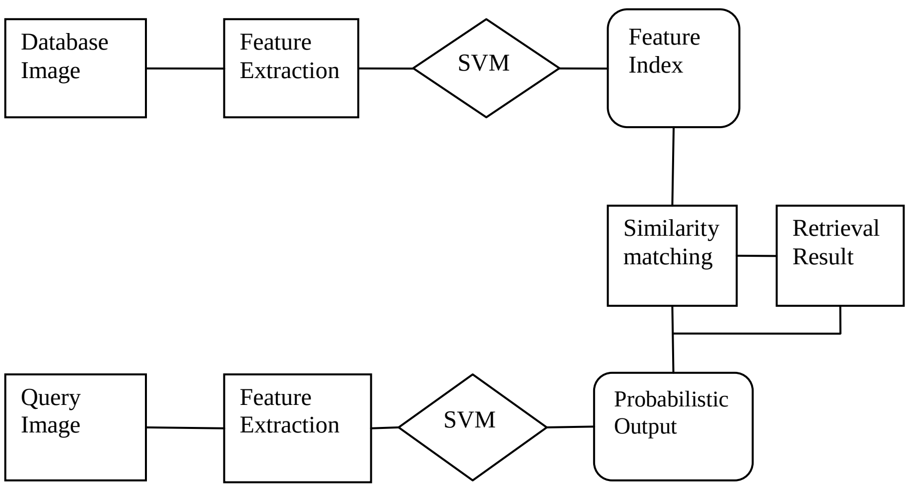

Fig 1: Architecture of Medical Image Retrieval

2.1 Feature Extraction

Feature extraction involves extracting the meaningful information from the images. So that it reduces the storage required and hence the system becomes faster and effective. For feature extraction CLD and EHD descriptors are used.

2.1.1 Color layout descriptor

The CLD is a very compact and resolution-invariant representation of color for high-speed image retrieval and it has been designed to efficiently represent the spatial distribution of colors. This feature can be used for a wide variety of similarity-based retrieval, content filtering and visualization. It is especially useful for spatial structure-based retrieval applications. This descriptor is obtained by applying the discrete cosine transform (DCT) transformation on a 2-D array of local representative colors in Y or Cb or Cr color space. The main functions of the CLD are basically Image-to-image matching or video clip-to-video clip matching [7].

The extraction process of this color descriptor consists of four stages:

- Image partitioning
- Representative color selection
- DCT transformation
- Zigzag scanning

2.1.2 Edge Histogram Descriptor

The edge histogram descriptor (EHD) represents the local edge distribution by dividing image space into 4×4 sub images and representing the local distribution of each sub image by a histogram. The fact that the EHD consists of the local-edge histograms only, makes it very flexible. In the sense of generating histograms, edges in all sub images are categorized into five types- vertical, horizontal, diagonal and non directional edges (namely edges with no particular directionality), resulting in a total of 5× 16 = 80 histogram bins. Each sub image is further divided into non overlapping square image blocks with particular size which depends on the image resolution. Each of the image blocks is then classified into one of the five mentioned edge categories or as a non edge block [8].

2.1.3 SVM for Multiclass Classification

Multiclass SVM aims to assign labels to instances by using support vector machines, where the labels are drawn from a finite set of several elements. A number of methods to generate multiclass SVMs from binary SVMs, Building binary classifiers distinguish between (i) one of the labels and the rest (*one-versus-all*) or (ii) between every pair of classes (*one-versus-one*). Classification of new instances for the one-versus-all case is done by a winner-takes-all strategy, in which the classifier with the highest output function assigns the class [9]. For the one-versus-one approach, classification is done by a max-wins voting strategy, in which every classifier assigns the instance to one of the two classes, then the vote for the assigned class is increased by one vote, and finally the class with the most votes determines the instance classification.

2.1.4 Similarity Matching

It is very difficult 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 different forms and may be complementary in nature. The most commonly used approach here is the linear combination of similarity matching of different features with predetermined weights. In this framework, the similarity between a query image *Iq* and target image *Ij* is described as

$\mathrm{Sim}(Iq, Ij) = \sum_F \alpha^F\ S^F\ (Iq, Ij\ )$ …… (1)

Where $F \in$ {Concept, Keypoint, EHD, CLD} and S^F (*Iq*, *Ij*) are the similarity matching function (generally Euclidean) in individual feature spaces and α^F are weights within the different image representation schemes within our framework[10].

2.1.5 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, previously computed category-specific feature weights (e.g.α^F) are used 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 shown in below algorithm [11].

Algorithm for Category-Specific Similarity Fusion Approach

(Off-line): Store manually-defined category specific feature-weights for similarity matching.

(On-line): For a query image Iq, calculate individual feature vectors f_q^F,

Where F Є {Concept, Keypoint, CLD,EHD }.

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

Combine the outputs by applying any of the combination rules (eg. Sum, max, prod, min).

Get the final category label as $w_m(q)$, m Є {1, . . . , M } of the query image.

Consider the individual features weights α^F for the query image category $w_m(q)$.

Finally combine the similarity scores with the weights based on similarity fusion. Finally return the images based on the similarity matching values to obtain a final list of images.

3. RELEVANCE FEEDBACK

Human visualization of image similarity is depend upon subjective, semantic, and task. Although content-based methods provide promising directions for image retrieval, generally, the retrieval results based on the similarities of pure visual features are not necessarily perceptually and semantically meaningful. Each type of visual feature tends to capture only one aspect of image property and it is usually hard for a user to specify clearly how different aspects are combined [12]. To address these problems, interactive *relevance feedback*, a technique in traditional text-based information retrieval systems, was introduced. With relevance feedback, it is possible to establish the link between high-level concepts and low-level features. Relevance feedback is a supervised active learning technique used to improve the effectiveness of information systems. The main idea is to use positive and negative examples from the user to improve system performance. For a given query, the system first retrieves a list of ranked images according to a predefined similarity metrics. Then, the user marks the retrieved images as relevant. 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. The typical scenario for relevance feedback in CBIR is as follows [13].

Algorithm: Typical scenario for relevance feedback in CBIR

Begin

Obtain the initial retrieval results of CBIR

Repeat until user satisfaction or result remains same

From user interaction, obtain the feedback from the users on prior results. Feedback is in the form of relevant or irrelevant to request.

If results found to be not satisfied

Learn the system through a feedback algorithm and hence results are refined

End repeat

End

4. PERFORMANCE METRICS

CBIR is essentially an information retrieval problem. Two of the most popular evaluation measures are the precision and recall [14]. The precision measures the proportion of the total images retrieved which are relevant to the query

$$Precision = \frac{No. of\ relevant\ images\ retrieved}{Total\ no. of\ images\ Retrieved}$$

The recall measure is defined as the fraction of the all relevant images.

$$Recall = \frac{No. of\ relevant\ images\ retrieved}{Total\ no. of\ relevant\ images\ in\ database}$$

High precision means that less irrelevant images are returned or more relevant images are retrieved, while high recall indicates that few relevant images are missed. Another way of presenting the performance of the system is by plotting precision and recall graph, in which precision values are plotted against values of recall. These graphs give a clear idea about the system performance. Some systems use average precision which provides a single value to compare the retrieval performance. In average precision, first precision is calculated for each retrieved relevant image. Then average precision measure is obtained by averaging these precisions over the total number of relevant objects.

5. RESULT

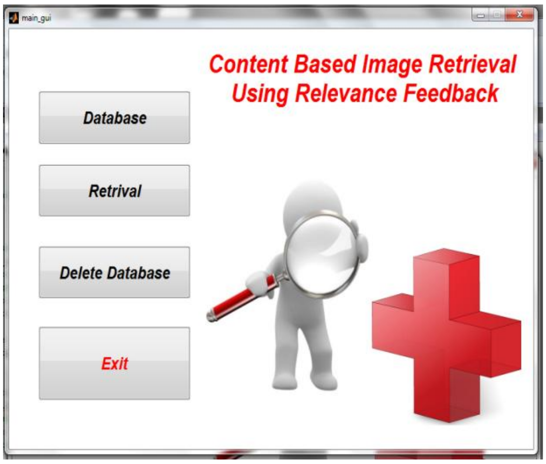

Fig 2: Main GUI

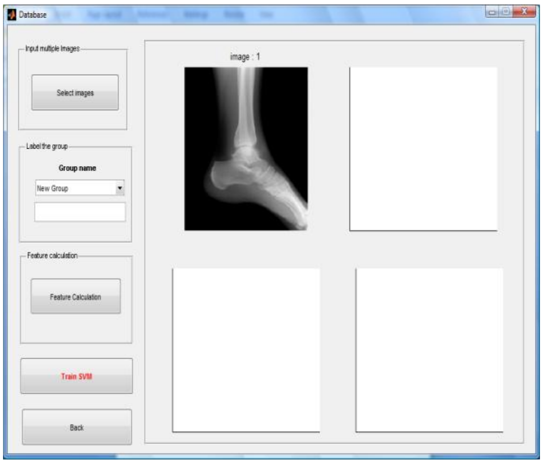

Fig 3: After Clicking "*Database*"

Fig 4: Creation of groups

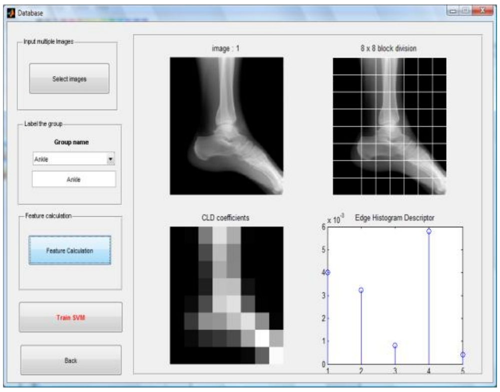

Fig 5: Feature Calculation

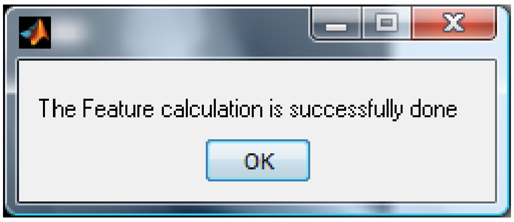

Fig 6: Notification for successful estimation of Feature vector estimation

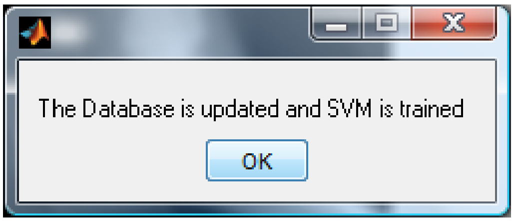

Fig 7: Notification for successful supervised training using SVM

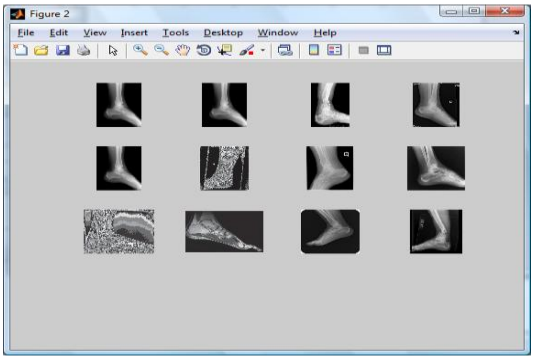

Fig 8: Retrieved images

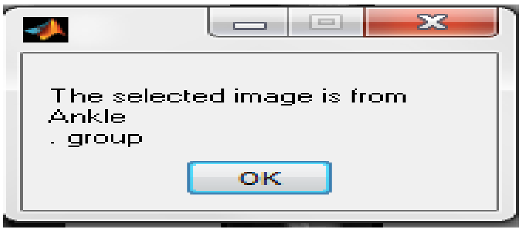

Fig 9: Retrieved images group

6. CONCLUSIONS

As multimedia technology is becoming more popular user not satisfied with current retrieval techniques so here we proposed CBIR using Relevance Feedback approach. The text-based approaches associate keywords with each stored image. These keywords are typically generated manually. There are two main disadvantages in this approach. One is that it requires a huge amount of human labor in the manual annotation especially when the image collection is large. The other one is that it is hard to precisely annotate the rich content of an image by humans due to perception subjectivity. This motivates to use content-based image retrieval (CBIR), where retrieval of images is guided by providing a query image. Multiclass Support Vector Machine (SVM) is used to reduce limitations of low level feature representation, here it categorize the probabilistic features to different classes. Relevance Feedback approach is used to reduce the semantic gap between low level & high level features.

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