CBIR FOR BIOMEDICAL IMAGE ARCHIVES USING EFFICIENT RELEVANCE FEEDBACK AND USER NAVIGATION PATTERS

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Abstract
Content Based Image Retrieval (CBIR) has been one of the most vivid research areas in the field of computer vision over the last ten years .Content Based Image Retrieval System is the solution for the problem of searching for digital images in large databases. Retrieval of images using CBIR has been a predominant scenario in the medical diagnosis. The impact of content-based access to medical images is frequently reported but existing systems are designed for only a particular modality or context of diagnosis. Contrarily, proposed concept of image retrieval in medical applications (IRMA) aims at a general structure for semantic content analysis that is suitable for numerous applications in case-based reasoning or evidence based medicine. The hybrid approach for relevance feedback incorporated into CBIR to obtain more precise results by taking users feedback. Existing relevance feedback-based CBIR methods usually request a number of iterative feedbacks to produce refined search results is impractical and inefficient in real applications. Existing Navigation-pattern-based algorithm (NPRF Search) merges three query refinement strategies including Query Point Movement, Query Reweighting, and Query Expansion, to converge the search space toward the users intention effectively. The proposed Navigation-Pattern-based Relevance Feedback with human behaviour in content based biomedical image retrieval(CBMIR-NPRF) can achieve the high retrieval quality of CBIR in a small number of feedbacks. Adaptive texture feature extraction algorithm is used and relevant images are retrieved by graph ranking algorithm in less number of iterations.

Keywords: Content-based image retrieval, low level features, relevance feedback, navigation pattern mining

I. INTRODUCTION

Interest in the potential of digital images has increased enormously over the last few years, fuelled at least in part by the rapid growth of imaging on the World-Wide Web. Typically, in the development of an image requisition system, semantic image retrieval relies heavily on the related captions, e.g., file-names, annotated keywords, and other manual descriptions. Unfortunately, this kind of textual-based image retrieval always suffers from two problems: high-priced manual annotation and inappropriate automated annotation. Problems with traditional methods of image indexing have led to the rise of retrieving images on the basis of low level features such as colour, texture and shape, now generally referred to as Content-Based Image Retrieval (CBIR)[7].Content-based means that the search makes use of the contents of the image themselves rather than relying on human inputted metadata such as captions or keywords.

Present system consists of retrieval based on indexing and keywords which are assigned to images by human categorizer. In medical diagnosis it becomes hard to compare images manually or by indexing. CBIR aids in medical diagnosis by identifying similar past cases. In medicine it would be very useful to be able to automatically diagnose disease from interpret medical images like X-ray, CAT scan, MRI, Histology etc. The medical professions store visual information in the form of X-rays, ultrasound or other scanned images, for

diagnosis and monitoring purposes. There are strict rules on confidentiality of such information. The images are kept with the patient's health records which are, in the main, manual files, stored by unique identifier. Much of the research effort related to images is undertaken in the medical physics area. The doctors make a diagnosis mainly according to medical knowledge and medical images.
Content-based image retrieval systems with relevance feedback require the integration of Image Processing and Information Retrieval. Current CBIR systems make use of relevance feedback techniques in order to reduce the so semantic gap between low level features and human visual perception . Using Navigation-Pattern-based Relevance Feedback with human behaviour (NPRF) [3] algorithm, the high efficiency and effectiveness of CBIR can be achieved in the large-scale image data like Biomedical Image Archives. These conventional approaches for image retrieval are based on the computation of the similarity between the users query and images via a query by example (QBE) system [5].The feedback procedure, called Relevance Feedback (RF), repeats until the user is satisfied with the retrieval results. Although a number of RF studies [9] [10] [11] have been made on interactive CBIR, they still incur some common problems, namely redundant browsing and exploration convergence. First, in terms of redundant browsing, most existing RF methods focus on how to earn the users satisfaction in one query process. That is, existing methods refine the query again and again by analyzing the specific relevant images picked up by the users. Especially for the compound and complex images, the users might go through a long series of feedbacks to obtain the desired images using current RF approaches with NPRF.

To resolve the aforementioned problems, A novel method named Navigation-Pattern-based Relevance Feedback with human behaviour[4] can achieves the high retrieval quality of CBIR with RF by using the discovered navigation patterns. In terms of efficiency, the navigation patterns mined from the user query log can be viewed as the shortest paths to the users interested space. According to the discovered patterns, the users can obtain a set of relevant images in an online query refinement process. Thus, the problem of redundant browsing is successfully solved In short, the discovered navigation pattern in NPRF Search can be regarded as an optimized search path to converge the search space toward the users intention effectively. As a whole, through NPRF, the optimal results can be attained in very few feedbacks.

II. RELATED WORK

Antani in [1] proposes advances in medical images for large image collections. An R&D division of the National Library of Medicine at the Lister Hill National Centre for Biomedical Communication, had research on CBIR for biomedical images. Here maintain an archive of over 17,000 digitized x-rays of the cervical and lumbar spine from the second National Health and Nutrition Examination Survey (NHANES II). In addition, developing an archive of a large number of digitized 35mm colour slides of the uterine cervix, research focuses on developing techniques for hybrid text/image query retrieval from the survey text and image data. Antani present the challenges in developing CBIR of biomedical images and results from their research efforts.

IBM's QBIC (Query by image content) system by Flickner in[7] QBIC allows queries on large image and video databases based on example images ,user constructed sketches and drawings , selected color and texture patterns .Offers retrieval by any combination of colour, texture or shape as well as by text keyword. Image queries can be formulated by selection from a palette, specifying an example query image, or sketching a desired shape on the screen. The system extracts and stores colour, shape and texture features from each image added to the database, and uses R*-tree indexes to improve search efficiency.

Human Behaviour Consistent Relevance Feedback introduced by Liu in [4] to bridge the well known semantic gap, relevance feedback as an effective solution. Existing methods follow a single-line searching philosophy, which may lead to a local optimum in search space. Simulating human behaviours, the proposed model enable the user to perform relevance feedback in three manners: Follow up, Go-back, and Restart. Each manner is a way for the user to provide the system with his or her opinions about search results. The accumulated feedback information can be used to refine the user query and regulate the similarity metric.

Haralick propose texture features in [2], Texture is an important feature of objects in an image. Haralick suggested the use of gray-level co-occurrence matrices (GLCM) to extract texture features from an image .Gray level co-occurrence matrix (GLCM) describes the relative frequencies with which two pixels separated by a distance d under a specified angle occur on the image. To accomplish texture analysis task, the first step is to extract texture features that most completely embody information about the spatial distribution of intensity variations in the textured image.

Haung et al. in [3] relevance feedback techniques were incorporated into CBIR such that more precise results can be obtained by taking user's feedbacks into account. However, existing relevance feedback-based CBIR methods usually request a number of iterative feedbacks to produce refined search results, especially in a large-scale image database. This is impractical and inefficient in real applications. Haung propose a novel method, Navigation-Pattern-based Relevance Feedback (NPRF), to achieve the high efficiency and effectiveness of CBIR in coping with the large-scale image data. In terms of efficiency, the iterations of feedback are reduced substantially by using the navigation patterns discovered from the user query log. In terms of effectiveness, 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), to converge the search space toward the user's intention effectively. By using NPRF method, high quality of image retrieval on RF can be achieved in a small number of feedbacks. The experimental results reveal that NPRF outperforms other existing methods significantly in terms of precision, coverage, and number of feedbacks.

III. PROBLEM FORMULATION

Existing relevance feedback-based methods usually request a number of iterative feedbacks to produce refined search results, especially in a large-scale image database. As the quality of Image retrieval degrades, proposed system efficiently retrieve relevant images of the query image, from the image database with less number of iterations .This is done by integrating human behaviour based relevance feedback with navigation pattern mining.

IV. SYSTEM MODEL

The block diagram for the proposed image retrieval framework based on the feature and the similarity level fusion is shown in figure 1. The query medical image should be any one of dropdown list (brain, lungs, chest, kidney, bones). Then low level features like energy, entropy, homogeneity, contrast i.e. f1, f2, f3, f4 respectively derive from gray level co-occurrence matrix (GLCM). Feature of input image is compared in similarity matching block with feature index of each image in database. Most similar images are retrieved .The retrieved images are judged by user to select relevant and non-relevant images. If user doesn't satisfies with current iteration, relevance feedback consistent with human behaviour is integrated to the marked relevant images. The model uses graph ranking techniques to retrieve most accurate image similar to query image. The navigation pattern mining will helpful for frequent users. The system will store the login details in log database and with help of if-then rules images are retrieved. The proposed system consists of following modules:

- Feature Extraction Module
- Comparison Module
- Human Behaviour based relevance feedback module
- Offline Knowledge Discovery Module,
- Image Retrieval Module

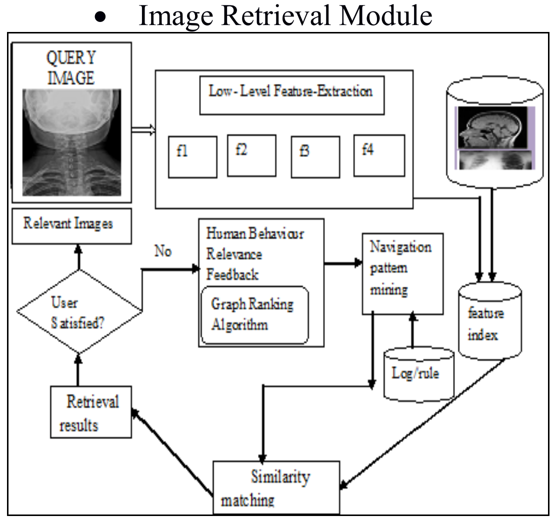

Fig.1 System architecture

A. Feature Extraction Module:

In pattern recognition and in image processing, feature extraction is a special form of dimensionality reduction. When the input data to an algorithm is too large to be processed and if the data is redundant then the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is called feature extraction.

The following Feature Extraction algorithm used gray-level co-occurrence matrices (GLCM) to extract texture features from an image.

Feature Extraction algorithm

Input: A set of X-Ray JPEG images
Output: Feature Vector corresponding to input image
Steps Involved:
1) Get Pixel matrix of input image.
2) Convert the Pixel matrix to gray scale matrix, Gray scale =0.299 * R + 0.587 *G + 0.114* B.
3) Convert the gray scale matrix to a Gray level matrix of order n.
4) Convert gray level matrix to a position matrix, pm[i][j].pm[i][j]=sum of diagonal occurrences of i,j.
5) Reduce a gray level matrix to a position matrix can be done using an appropriate position vector.
6) Create Co-occurrence matrix from position matrix, cm[i][j]. cm[i][j]=pm[i][j]/∑(pm),where pm is the position matrix.
7) Extracting features from Co-occurrence matrix.

Features calculated from the co-occurrence matrix are:

- Energy=$P_{dr}^2(i,j)$
- Entropy=$P_{dr}(i,j)\log P_{dr}(i,j)$
- Contrast=$|i-j|^k P_{dr}^2(i,j)$ (typically k=2,i=1)
- Homogeneity=$P_{dr}(i,j)$

Where P_{dr} is the co-occurrence matrix.The extracted features are together called a Feature Matrix.

B. Comparison Module

In the comparison phase, first the feature vector of the input image is extracted. Then this feature vector is compared with that of the images stored in the database to find a function called the Euclidean distance. The matching of the two images is determined by this vector. The visual similarity is increased by the decreasing value of Euclidean distance. Euclidean distance of two feature vectors,

D=sqrt (sum of (pow (f_{1i}, f_{2i}), 2)), Where f_i is the i^{th} feature in the feature vector.

C. Human Behaviour Based Relevance Feedback Module

A human behaviour consistent relevance feedback model is used, which allows the user to perform three kinds of feedback operations, as well as explicit relevance judgments. The graph ranking algorithm is in co-operated to model the retrieval process.

Graph Ranking Algorithm

Input : Feature Vector corresponding to the image.
Output : Re-Ranked Relevant Images.
Steps Involved :
1) Calculate the Ranking score vector f_n^*

$$f_n^* = r_{(n+1)} + b_{(n+1)}$$

2) Update Initial label vector as:

Follow up, $y_{(n+1)} = f_n^* + r_{(n+1)}$

Go back, $y_{(n+1)} = f_{(n-1)}^* + r_{(n)}$,

Restart, $y_{(n+1)} = \begin{cases} -1, & \text{Irrelevant} \\ 0.5, & \text{Relevant,} \\ 0, & \text{otherwise} \end{cases}$

3) Combine the feedbacks with the updated label vector to learn a desired distance metric, i.e. dis(.) as in equation**.**

$$dis(x,y) = dis^2(x,y)_A = ||x-y||^2_A = ((x-y)^T A(x-y))$$

4) Construct the similarity matrix $W \in \Re^{N2}$ as:$W_{ij}=\exp[-dis(x_i , x_j)] /\sigma$,where $\sigma>0$, $W_{ii}=0$, and dis(.) is certain distance metric.

5)Obtain the ranking score of each point according to updated Similarity Matrix

D. Offline knowledge discovery

Learning from users behaviours in image retrieval can be viewed as one type of knowledge discovery. Consequently, this phase primarily concerns the construction of the navigation model by discovering the implicit navigation patterns from users browsing behaviours. This navigation model can provide image search with a good support to predict optimal image browsing paths. The databases in this phase can be regarded as the knowledge marts of a knowledge warehouse, which store integrated, time-variant, and nonvolatile collection of useful data including images, navigation patterns, log files, and image features. The knowledge warehouse is very helpful to improve the quality of image retrieval. Note that the procedure of constructing rule base from the image databases can be conducted periodically to maintain the validity of the proposed approach.

E. Image Retrieval Module:

In a retrieval operation in an image database, a particular feature of the query image, Q, is used for (dis-) similarity measurement with the same feature of a database image,I. Repeating this process for all images in the database, D, and ranking the images according to their similarity distances yield the retrieval result.

V. EXPERIMENTAL RESULTS

The experiments were implemented in java, running on a personal computer with Pentium 4, 2.4 GHz processor and 512 MB RAM. The project Content Based Biomedical Image Retrieval starts with a login screen to provide security. The users can be doctors, staffs or students of the medical diagnostic centre. After the successful login, the menu is shown from which the tasks can be chosen according to the requirement. Search By Image-The input query image (jpg file) is uploaded from a folder, IRMA-NPRF will retrieve most similar images corresponding to user query efficiently with less number of iterations. The user should enter the folder in which the images are stored and then processing includes: extracting the features from the images, comparing the extracted features with the normal value, displays the Matching status.

VI. Performance Analysis

The effectiveness or performance of a CBIR or RF scheme can be specified by several objective measures. A standard pair of performance measures is precision (Pr) and recall (Re). They are defined as follows:

$$Pr = \frac{\text{(Fixed number of total returned images)}}{\text{(Number of retrieved relevant images)}}$$

The effectiveness of the relevant feedback procedure was evaluated for medical x-ray image retrieval experiments. The medical image was tested using a data set of 100 images, containing 20 possible images in each set. All 5 data sets were selected to be included in the CBIR and RF retrieval problem. Three basic retrieval rounds were evaluated, with round 1 being the CBIR step. The query vector was changed 5 times,using a different medical image query for each retrieval experiment. The ensemble recall results are presented in the bar chart of Figure 2.

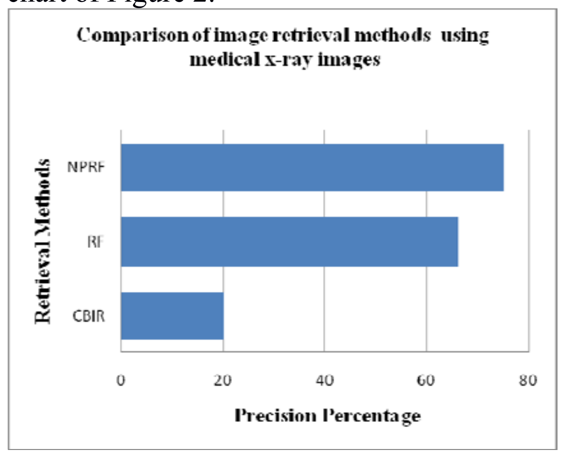

Fig 2: Performance Analysis

VII. CONCLUSION AND FUTURE WORK

New software is investigated for content based biomedical image retrieval, In line with a new algorithm for relevance feedback with human behaviour for huge biomedical image database retrieval. Thus semantic gap between low-level image features and user visual perception is reduced some extent. The desired user image similar to query image is retrieved effectively in less number of iterations compared to the previous systems. The comparison module in the new system helps users to compare two images and diagnosis of x-ray images with previous cases can be done efficiently. Thus doctors can easily diagnosis, if the same case already exists by comparing the two images. Comparing to classical algorithms like SVM GRDL (Graph Ranking Distance Learning), QPM (Query Point Movement), and DML (Distance Metric Learning) are performed as the single-line search which may lead to a local optimum in search space. Human behaviour consistent relevance feedback model for image retrieval, only take "Follow up" operation at each round of feedback will produce better results than others

In the Future the proposed method can be scaled by utilizing parallel and distributed computing techniques. Second, we can integrate patients profile into NPRF to further increase the retrieval quality.

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