MIRAGE: An E-repository of Medical Images for Learning Biomedical Informatics

Xiaohong Gao
School of Engineering and Information Sciences,
Middlesex University
London, NW4 4BT, UK
x.gao@mdx.ac.uk

Yu Qian
School of Engineering and Information Sciences,
Middlesex University
London, NW4 4BT, UK
y.qian@mdx.ac.uk

***Abstract*— Although around 5 billion medical image studies were carried out in 2010, there is still a shortage of medical image databases that are available for students due to well-know reasons. To this end, an online image repository, MIRAGE, has been developed for teaching and learning biomedical informatics, which accommodates collections of published medical images of both 2D and 3D. The facilities of domain-based, atlas-based, and content-based retrieval (CBIR) are implemented to proffer the search in the repository. The novelty of the system is that not only a collection of 3D brain images is warehoused, but also CBIR for 3D is developed coupled with 3D visualization, leading to a versatile educational material, leading to future tele-education. The initial evaluation of the repository by users of both research students and lecturers has proven its positive impact.**

Keywords - medical image data base; image retrieval; CBIB; image labeling.

I. INTRODUCTION

With the advances of Internet technology, e-learning and e-teaching have flourished and borne fruits in a number of applications. In recent years, many online learning systems are available to students and have played an important part in assisting them learning. These systems usually tend to be in general purpose in order to meet majority students' need, e.g., institutional e-print repositories providing published materials of papers, reports, etc.. However, sometimes, subject-based databases are in demand by a number of groups, leading to the development of discipline-based systems. For example, an online system, ENDOCAS [1], has implemented imaging assisted surgery (IAS) systems to provide *information help*, *action help* and *training help* by offering assistance on planning surgical intervention, integrating mechanic components of the robots, and simulating complex environment for surgical training respectively. Whereas in [2], a medical image repository has been integrated with a web-based learning system, providing web-based tools to assign and assemble the contents of medical images.

E-learning has not only offered a new way of learning, but also brings all the advantages that an internet can offer to the learning and teaching process, such as flexibility, accessibility and straightforwardness. On the other hand, however, although medical imaging has revolutionized health care delivery in the last 30 years, and around 5 billion medical imaging studies were conducted worldwide [3] in 2010 alone, there are very limited numbers of online databases available, due to the well known reasons of patients' privacy and security, prompting the development of purpose-built repository for the benefit of both students and lecturers.

At Middlesex University in the UK, a new MSc programme was introduced in 2007 on BioMedical Modelling and Informatics (BMI) that has been attracting an increasing number of students. During the course of studying and conducting final projects, a large number of medical images had been employed in addition to many other forms of data. Following a successful bid to JISC [4] at the UK in 2009, an attempt to establish a subject-based repository started. The main aim of the online repository, MIRAGE, is to develop a subject-based repository of medical images, in the immediate term, benefiting MSc students who are on the programme of Biomedical Modelling and Informatics (BMI) at Middlesex University at the UK. It is anticipated the repository will be adopted by and serve the community in the middle term. As a result, MIRAGE, acronym of Middlesex Image Repository with a CBIR Archiving Environment, has been up and running and is available at [5].

The structure of the paper is organized as follows. Methodology is detailed in Section II, which is followed by Evaluation of Section III. Proceeding Conclusions and Discussion, the Section of Results is given in Section IV.

II. METHODOLOGY

Figure 1 demonstrates the interface of the system.

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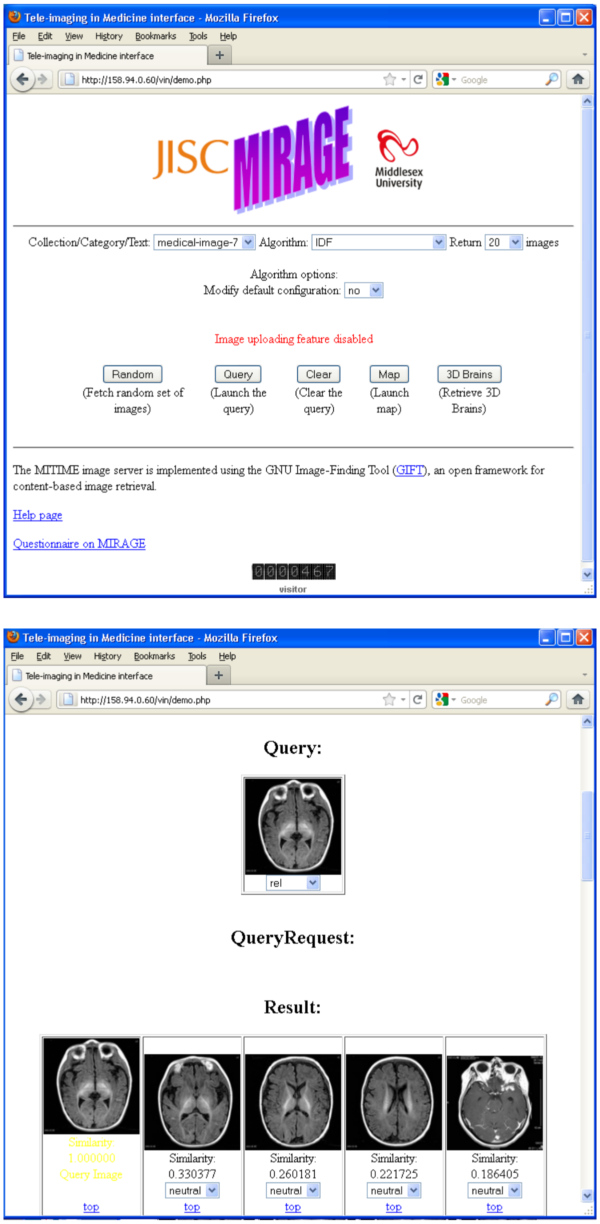

Figure 1. The interface of MIRAGE system at http://image.mdx.ac.uk/vin/demo.php . Top: menu interface; bottom: retrieval results for a query.

The repository began with the ingestion of a large collection of medical images into the existing server that then had only archived a few hundreds of images of limited domains. Since many image data are without any textual labeling, archiving image data is different from that to textual files that can be indexed using a few key words embedded in the files. This deposition stage hence included the establishment of both feature and image databases. A number of approaches in extracting features had been applied in pre-processing images. By building on from an open source software GNU GIFT (GNU Image-Finding Tool [6], the online system currently not only facilitates a means to search images by their contents, notably content-based image retrieval (CBIR), but also interfaces with OASIS+, the online teaching system at Middlesex University to ensure it can be accessed easily.

The system at present accommodates over 100,000 images. All the collected images in the server comply with the informed consent requirement and consist of 2D medical images, 3D brain images (CT, MR and PET) and 4D cardiovascular ultrasound images. MIRAGE adapts an open framework of GIFT for the retrieving of 2D medical images. By introducing the automatic image annotation, MIRAGE offers the possibility of combining visual content with keywords to achieve the higher level of semantic search. In addition, MIRAGE has developed its own method for 3D brain images retrieval to complement to the existing 2D medical image repositoryCBIR for 3D Brain Images.

A. The System

Figure 2 illustrates the infrastructure of MIRAGE. To address the problems that current text-based image retrieval systems suffer, MIRAGE integrated the methods of both content-based image retrieval (CBIR) for 2D and 3D collections and automatic image annotation to label the images with its keywords, leading to a higher level of semantic search. It therefore consists of three modules as shown in Figure 2, with components of image annotation, 2D image retrieval and 3D image retrieval.

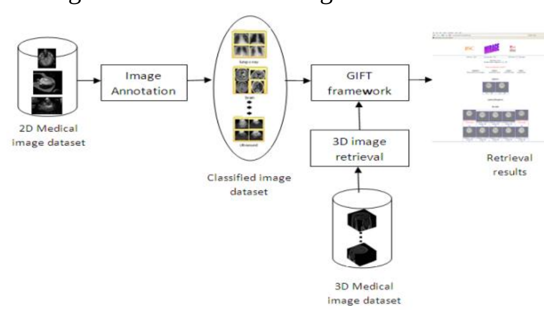

Figure 2. The Framework for MIRAGE.

Built on the open source GNU Image Finding Tool (GIFT), the online database is based on the Query-by-Example (QBE) paradigm coupled with user-relevance feedback facility whereby retrievd images most closely resemble a query image in appearance (i.e., the content that an image is carrying). Two algorithms have been implemented for indexing image collections, which are IDF (Inverse Document Frequency) and Separate Normalisation. IDF is a classical method and is based on counting the number of documents in the collection being searched, which contain (or are indexed by) the terms in question [3]. The inverted-file database system has been applied in text retrieval systems, giving rise to the efficiency when

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employed in an image system. The weighting features are calculated as in Eq. (1) [7].

$$feature\_relevance_{qj} = \frac{1}{N}\sum_{i=1}^{N}(tf_{ij}R_i)log^2(\frac{1}{cf_i})$$
$$image\_score_{kq} = \sum_j tf_{kj} feature\_relevance_{qj} \quad (1)$$

where tf_{ij} is the term frequency of a feature in either a query or a resultant image, cf_i the collection frequency of a feature, whereas q is a query containing N images ($i = 1,2 \ldots N$) with relevance R_i = 1(relevant) or -1(irrelevant). In addition, k is a retrieved image, j the index of a feature, and R the user-relevance of a query image with value between [-1,1].

On the other hand, feature normalisation is required to compensate the scale disparity between the feature components that are defined in different domains. On the client side, a web page based interface is given. Whist the client-server communication is achieved using the XML-based Multimedia Retrieval Markup Language (MRML). All client-server communication, including queries from the client or results returned by the server, is realised using message passing. Consequently, the client can be implemented in any programming language. The current MIRAGE client is implemented using PHP (Personal Home Programming) language to generate dynamic web pages for the client web browser.

B. Image Annotation based on Domains

One feature that the MIRAGE has is its ability of image annotation fully automatic, in order to achieve a higher level of semantic search, and to organize and categorize images of interests. Automatic image annotation is the process by which a computer system automatically assigns metadata in the form of captioning or keywords to a digital image. At present, the Bag-of-visual-Words (BoW) [8] paradigm becomes very popular and has been successfully applied for image categorization. By transforming images into a set of 'visual vocabulary', images are represented using the statistics of the appearance of each word as feature vectors, upon which the learning of an image classification rule could be achieved as a classifier. This idea has been adopted in the MIRAGE system coupled with SIFT sparse coding approach [9], which is achieved in the following four steps that is also illustrated in Figure 3.

- Step 1 -- the visual features are extracted from local patches of each image in the training dataset , leading to the construction of a visual dictionary of *codebook*;
- Step 2 -- to quantize the visual features of the image dataset into discrete *'visual words'*.;
- Step 3 -- an image is represented as a unique distribution (e.g. a histogram) over the generated dictionary of words; and
- Step 4 -- image representations of the training dataset obtained in Step 3 are applied to train the classifiers using supervised machine learning methods. Finally, the trained classifier automatically allocates new images into corresponding categories and hence labels them.

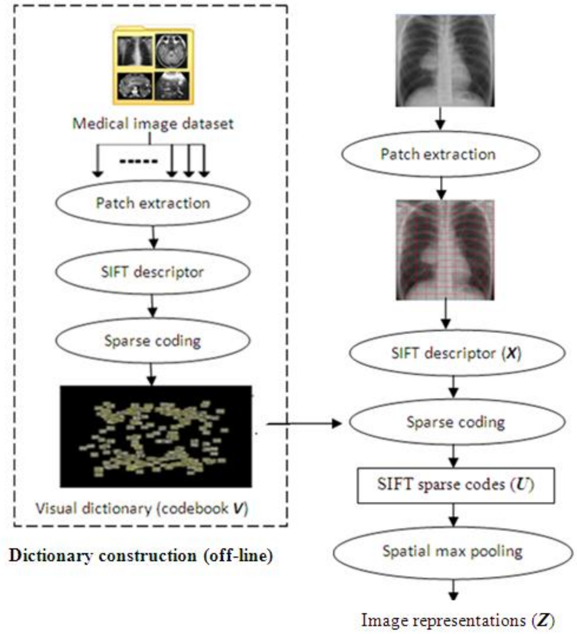

Figure 3. Dictionary construction and image representations.

Unlike traditional BoW paradigm, sparse coding is employed in the MIRAGE instead of vector quantization (VQ) to extract the SIFT descriptors of local image patches. Furthermore, instead of using histograms, multiple scales of max pooling are employed as an image representation by the use of simple linear support vector machines (SVMs). In comparison with the SVMs using nonlinear kernels, e.g. histogram intersection kernels, linear SVMs can dramatically reduce the training complexity while maintaining a good performance.

C. CBIR for 3D Brain Images

For 3D brain images, four texture based methods are implemented as shown in Figure 4, including , 3D Local Binary Pattern (LBP), 3D Grey Level Co-occurrence Matrices (GLCM), 3D Wavelet Transforms (WT) and 3D Gabor Transforms (GT) as detailed in [10, 11]. Figure 5 depicts the flowchart of CBIR for 3D images.

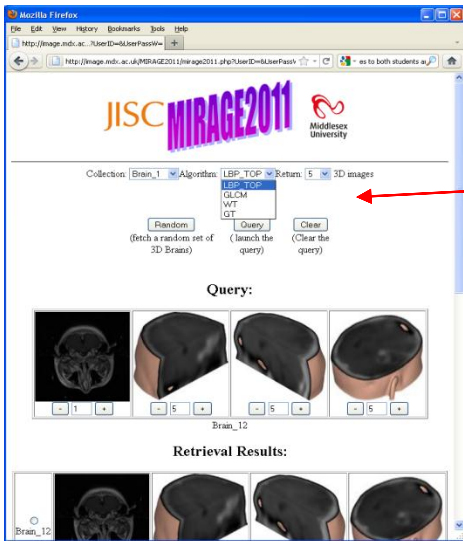

Figure 4. The interface of 3D images retrieval with four texture-based methods (arrowed) and visualization.

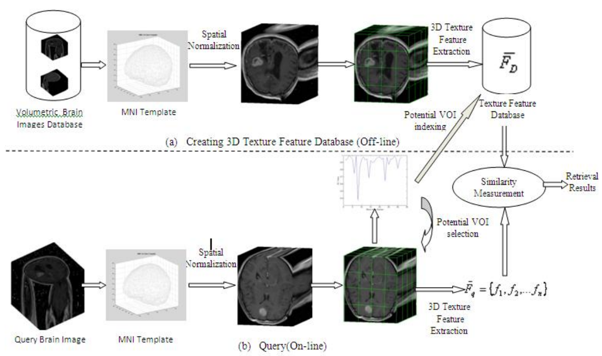

Figure 5. Framework for Content-based 3D Brain Image Retrieval

As shown in Figure 5, the collection of 3D brain images firstly underwent a pre-processing stage to normalize them into the same resolution before the indexing stage. After spatial normalization of volumetric brain data into a standard template, the data are then divided into 64 non-overlapping equally sized blocks, from which, 3D texture features are extracted to create a feature database. On the query side, a pre-processing stage is introduced to detect the potential VOI of lesions after spatial normalization from a query image. Subsequently, the extraction of 3D texture features from a query only takes place from these potential sub-blocks that, in the retrieval stage, are in turn compared with the corresponding features in the feature database to obtain retrieval results. Figure 6 demonstrates an example retrieved using different texture approaches [12].

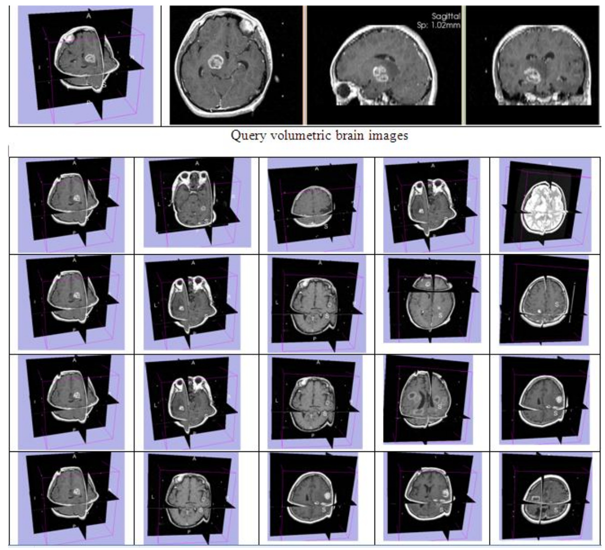

Figure 6. Retrieved results in top 5 ranking from
3D GLCM (row 1), 3D WT(row 2), 3D GT (row 3), and 3D LBP (row 4).

The judgement of each approach is subject to the applications of the retrieval task as to which of the measures of size, location or shape plays more important role than the others.

III. EVALUATION

The system evaluation is carried out from both objective and subjective prospects. As an objective evaluation, a number of statistic measures are applied to evaluate the research methods, such as Average Accuracy Rate (AAR) for image classification and Mean Average Precision (MAP) for image retrieval. On the other hand, the subjective evaluation is accomplished by using a survey questionnaire conducted by the students and researchers/lecturers at MU who have employed the medical image repository MIRAGE in their teaching and research.

To assess the effectiveness of image classification, a confusion matrix is firstly created as explained at [13]. Then with regard to the performance of image retrieval, traditional measures of Precision (P) and Recall (R) are worked out. By representing P-R graph using one value, MAP value is applied to measure overall performance for all queries and is calculated as Eq. (2).

$$\text{Mean Average Precision (MAP)} = \frac{1}{M}\sum_{i=1}^{M} AP_i \qquad (2)$$

where M is the total number of the queries, AP_i is the AP value for the i^{th} query, which is formulated as Eq. (3).

$$\text{Average Precision (AP)} = \frac{1}{N_r}\sum_{j=1}^{N_r} P_j \qquad (3)$$

Upon which N_r is the total number of relevant images in a dataset for a query, and p_j is the precision when retrieving the j^{th} relevant image. A P-R graph together with a MAP value is therefore applied to evaluate the performance of CBIR for 2D and 3D images in this project.

In addition, an on-line questionnaire as given on the interface (e.g., the bottom line at Figure 1) is designed in the hope to subjectively evaluate and further improve the system. The questionnaire consisted of 15 questions organized in three categories on i) the general information on the use of MIRAGE; ii) the evaluation of system usability; and iii) the comments/recommendations in regarding to the features of MIRAGE.

IV. RESULTS

A. Results on Image Annotation

In order to train a codebook for image annotation, a training dataset is firstly selected containing 1000 images that are randomly chosen from our medical image repository. Then 200,000 random patches are collected from these images. Subsequently, from each patch, SIFT descriptors are extracted, yielding a feature database that has the size of 200,000*128 elements, which are finally applied to train the codebook with the size of 1024*128 in terms of feature vectors.

With respect to ground truth for image annotation, six domain names are defined at the highest level, including brain, lung (x-ray), microscopy, abdomen, ultrasound and graph respectively. Each category is allocated 100 images as ground truth with each half as being training and testing sets respectively. The classification results for the six categories are visualized in a confusion matrix in Table 1.

TABLE 1: CONFUSION MATRIX FOR THE SIX MEDICAL IMAGE CATEGORIES, WHERE B, L, M, A, U, G REPRESENT CATEGORIES OF BRAIN, LUNG, MICORSCOPY, ABDOMEN, ULTRASOUND, AND GRAPH

		Classification Results						AR
		B	L	M	A	U	G	(%)
Ground Truth	Brain	48	0	2	0	0	0	96
	Lung (x-ray)	0	50	0	0	0	0	100
	Microscopy	0	0	49	0	1	0	98
	Abdomen	0	0	0	50	0	0	100
	Ultrasound	0	0	0	0	50	0	100
	Graph	0	0	0	0	0	50	100
ER(%)		0	0	3.92	0	1.96	0	

The values in the last column of Table 2 are the Accuracy Rate(AR) values for each class, whereas the values in the last row are the Error Rate(ER) for each class. The Average Accuracy Rate (AAR) for all classes is 99% (297/300), and Average Error Rate (AER) is 1% (3/300), demonstrating the approach of annotation being very efficient.

B. Results for 3D image retrieval with CBIR

Figure 7 plots the average Precision Recall Graph for ten queries across the whole datasets (around 100 of 3D MR brain images). The MAP and average query time by using the approaches of 3D GLCM, 3D WT, 3D GT and 3D LBP are given in Table 3. The query time amounts to the time spending on both feature extraction and retrieval, the results based on the programs that are written in MATLAB R2009a running on a computer with specifications of Intel P8600 CPU of 1.58GHz with 3.45GB RAM.

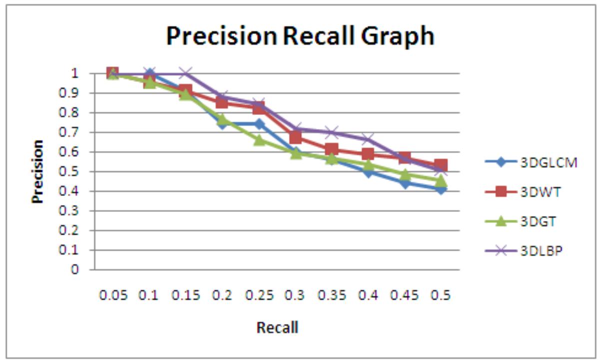

Figure 8. Average precision recall graph for ten queries.

TABLE 2. MAP AND QUERY TIME FOR 4 TEXTURE REPRESENTATION METHODS.

Methods	**Mean Average Precision (MAP)**	**Query time**
3D GLCM	0.690	10.96s
3D WT	0.749	1.22s
3D GT	0.691	10.77m
3D LBP	0.786	0.21s

The above results show the approach of LBP not only can achieve precision rate by up to 78% but also can perform retrieval in real time with sub-second speed. All these four methods are implemented in the system giving users the choices.

C. Results on Subjective Evaluation

An on-line questionnaire is applied to subjectively evaluate and thereafter further improve the system. This questionnaire comprises three parts covering the general impression of the repository, system evaluation and comments on the system respectively. This survey has been carried out by MSc students and researchers at MU, by which a total of 15 people participated.

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In terms of expectations, all respondents 'agreed' (80%) or 'strongly agreed' (20%) with the retrieved results, suggesting that the system meets users’ expectations. They all 'agreed’ (30%) or 'strongly agreed' (70%) that the system was fast and easy to use, and was useful to teaching and learning. On the other hand, users of 60% and 40% strongly agree or agree that the system is useful for teaching and learning.

V. Conclusion and Discussion

This project integrates the existing technologies to implement a versatile, useful and easy to operate system for teaching and learning, The techniques include GIFT framework for CBIR and image annotation using SIFT sparse codes while developing its own re-useable module retrieval and visualization of 3D brain images.

Works on 4D ultrasound images with CBIR facility currently is underway with future working including visualization of 3D video images (=4D) while performing the retrieval.

With respect to the issue of security, the system is controlled via password. Because it is not connected to any clinical systems and the images are without any identifications, the risk to patients’ privacy is very limited. Furthermore, all collections are from published work on the search of implying information in images, i.e., data mining. With this in mind, the developed system MIRAGE is wide open to the communities of research, learning and teaching, especially when remote teaching and leaning prevail.

On the other hand, the source code for 3D image retrieval and visualization are to be realised to the public to benefit the community that are carrying out similar work.

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