Integration of Content Based Image Retrieval System with PACS

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ABSTRACT

Content-based image retrieval (CBIR) provides a flexible means of searching a digital image library based on the description of the desired image. In this paper, we integrate CBIR, RIS, and HIS in PACS to allow retrieving images of similar features. Once the system finds the related images, the embedded CBIR retrieves the radiological reports and medical records of the output images, which can be used to increase diagnostic accuracy. The CBIR system is implemented on a separate server based on multi-resolution image matching. To reduce the retrieval loading on the server and network shanks, a procedure to use copies of images that are temporarily located in some workstations in the PACS is applied. These copies are stored on a temporary database space created on the different workstations. A new image retrieval management server contains image IDs in the database and the IP addresses of the workstations containing temporary image copies. Data on the management server are continuously updated with each addition or retrieval operation. When a display workstation needs a specific image, it sends a request with the required image ID to the management server, which in turn replies with the IP of the workstation containing the inquired image ID.

Keywords: PACS, content based image retrieval, image classification.

1. INTRODUCTION

Compared to the time before the last few decades, the degree of uncertainty in medical diagnosis has dramatically decreased. Medical imaging plays an essential rule for improving medical diagnosis. Now, physicians have access to a large number of imaging modalities with unique diagnostic characteristics for each. These medical imaging modalities not only provide non-invasive description of organs and anatomical cross sections, but also they provide information about physiological status, measuring brain functional activities and blood flow within the heart and the vessels.

A great amount of research work has been devoted to the development of different medical imaging modalities. The research aims to increase image quality, decrease image reconstruction time, increase the safety of the imaging systems, and maintain the reliability and portability of imaging modalities. Moreover, research work is growing fast to maximize the amount of extracted diagnostic information from medical images with applications in diagnosis, clinical research, and medical education. Based on this direction of research, systems such as picture archiving and communication systems (PACS), hospital information systems (HIS), radiology information systems (RIS), patient information systems (PIS), telemedicine, and teleradiology have been developed and matured commercially.

The advances in PACS performance and capabilities depend on research work in many areas that include electronics and computer engineering fields. Multimedia database is one of these fields since the archiving system in PACS can be looked at as a subset of the class of multimedia database systems. In the past few years, the area of content-based image retrieval (CBIR) has received an increasingly higher interest from multimedia database researchers. The techniques of CBIR provide flexible means of searching within digital images based on the description of a desired image or class of images. This description can take many forms such as comparison to a reference image or even a set of qualitative features representing quantitative pictorial features.

CBIR has been developed and implemented in several multimedia database systems such as the IBM QBIC system, developed at the IBM Almaden Research Center, the Virage System developed by Virage, Inc., and Photobook System developed by the MIT Media Lab. In these systems, a feature vector is generated for every image in the database. This feature vector must be smaller than the original image. In order to retrieve images from the database, the feature vector is calculated for the input image and compared to previously generated feature vectors to determine the vectors much similar to the input vector for retrieving their images from the image database. The key factor in CBIR systems is the selection of the feature vector, which provides a good representation for the image in minimum size and minimum calculation time for vector generation and matching. In this work, we integrate CBIR for medical images with PACS, RIS and HIS, and provide a new design reduce medical images retrieving time using copies of images that are temporally located in some workstations in the PACS. The Medical CBIR is developed for retrieving the images that contain similar features in common which lead to same diagnosis as the input image or at least the similar diagnostic features. Once the system finds the related images, the radiological reports and medical records of these images are retrieved and provided to the radiologist. This feature allows radiologists to make use of previous cases diagnoses in order to increase his/her diagnostic accuracy. The feature is also valuable for training junior radiologists.

2. MEDICAL CBIR

In the design of a CBIR system for medical field we are faced with a number of unique constraints. The following is the definition and analysis of these constraints:

1. *Local versus Global Features*: Using global parameters such as color histogram and texture values cannot provide good results in medical imaging. This is because in medical images the local texture, shape, and/or brightness of some small objects or parts may have a high diagnostic value[1].
2. *Large number of different imaging modalities/modes*: The sources of medical images are many. Examples of such sources are diagnostic ultrasound, X-ray computed tomography (CT), magnetic resonance imaging (MRI), digital subtraction angiography (DSA), positron emission topography (PET), magnetic source imaging (MSI), conventional X-ray, and computed radiography (CR) [2]. Moreover, within each modality, there are several modes by which the image is acquired. Each mode differ significantly from the other modes, e.g., contrast modes in MRI. Due to the wide differences between the physics underlying these modalities, It is rather difficult to design CBIR system that works for all modalities using the simple feature vector approach.
3. *User interactivity*: The system must allow the user to determine the part(s) with high diagnostic value since no automatic system has been able to do that successfully.
4. *Huge size of image database*: The technique must offer fast performance since a full-scale picture archiving and communication systems (FS-PACS) of a mid-size hospital (around 600-800 beds) would easily require 1 TBytes of digital data per year in its image archive or library.

Based on the constraints above, we will address a particular aspect of the problem at hand defined as building a CBIR system dedicated for MRI, CT and X-ray images. This system must deal with local features of the images and allow the user to interactively locate the regions with high diagnostic values. The system matching strategy must be fast and the extracted features must be suitable for storage in a database.

Compared to Histogram based CBIR systems, wavelet based CBIR systems are more reliable for medical images. In histogram based systems, feature vector neglects location information. This drawback in histogram based systems may lead to considering two images to be very similar, even though they represent very different diagnostic information. Similar to histogram based systems, Global texture based systems also neglect location information. On the other hand, based on the nature of the wavelet transform, which preserves the location information, wavelet based CBIR systems can be considered more suitable to representing medical images[6-7].

Searching the available CBIR literature, we observe a number of systems that stand out for their unique features. Examples of such systems are the system implemented by the University of Washington for multi-resolution image querying [4], and the system developed at Stanford University which was called WBIIS (Wavelet-Based Image Indexing and Searching) [3]. Both systems are considered wavelet-based CBIR systems. The system of the University of Washington is based on Haar wavelets, while Stanford University WBIIS is based on Daubechies wavelets. Both systems are designed for general-purpose image indexing and searching. Therefore, their performance becomes very poor when applied on medical images since the constraints in the problem definition stated above are not properly addressed.

Here, we propose a wavelet-based system that is more suitable for medical CBIR systems. Figure 1 shows a block diagram of this system. As shown in this diagram, the system consists of the following components: preprocessing, feature extraction, matching, final selection, in addition to complete case images and medical report retrieval. Each one of these blocks will be described in more details in the following subsections.

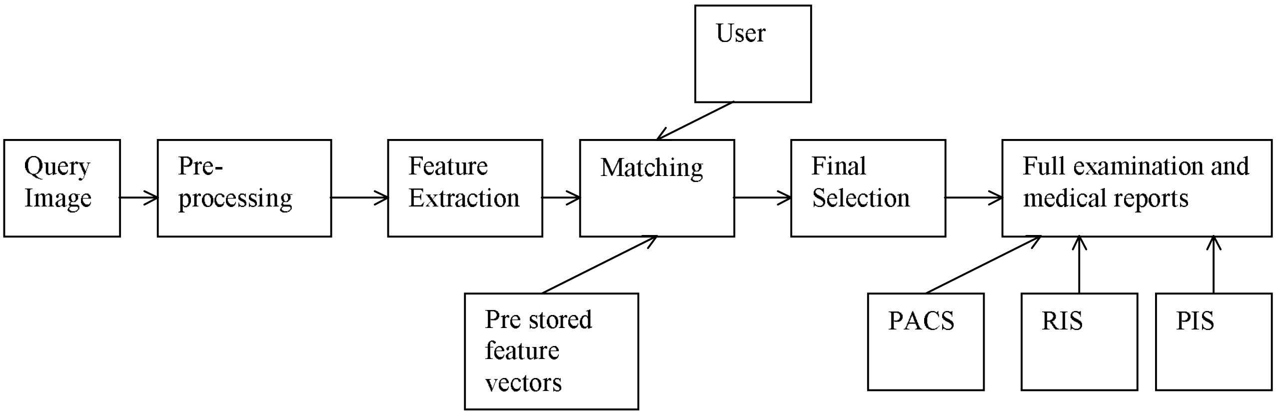

Figure 1: System block diagram

2.1 Preprocessing

In our system, we work with CT/MRI/X-ray images stored in PACS. The size of the images used may be up to 1024×1024 with up to 12-bit gray scale. In the first step of preprocessing, the images are re-sampled to a smaller size of 256×256 using bilinear interpolation. The input image is overlaid with a grid of 256 × 256 points. The input image is then sampled at each grid point to determine the pixel color of the output image. When grid point lies between input pixel centers, the color value of the grid point is determined by linear interpolation between adjacent pixel gray levels both in the vertical and horizontal directions. The gray levels are then re-quantized to have up to 256 gray levels (i.e., 8-bit gray scale). These normalized versions of the images will be used only for building the corresponding feature vectors and will not be stored in the PACS. Due to the huge size of the database, the original images are the only ones that are stored in the archiving system in order to reduce storage size. Moreover, the normalized images cannot replace the original images in the database since the latter may have better resolution and color quality and consequently of more diagnostic value.

In the second step, we apply noise reduction filtering on the query images. Since the database images are already used for diagnosis, they are assumed to be of high quality and no filtering is needed for them in general. The denoising process is applied when the variance in background region of the query image is higher than a certain threshold. All CT, MRI and X-ray images have a common appearance of a dark background with one or more structures on top of it. The noise adds energy to the image specially to the background. Consequently, this energy causes a bigger error in the matching stage. Among the denoising techniques, Low-pass filtering or averaging techniques reduce the sharpness of the boundaries and edges in addition to re-distribution of their energy. More complex denoising techniques such as Wiener filters or wavelet denoising cannot be used due to their relatively high computational cost, which slows down the speed of the entire procedure. Therefore, a 5×5 median filter has been selected and found sufficient for this application. It is more robust for boundary values in the area under the mask and performs well in reducing the noise energy especially in the background area.

One of the advantages of wavelet techniques over other global color indexing techniques, such as global histogram based techniques and texture-based techniques, is that the feature vector contains spatial information given that it is a color layout image indexing system. This feature, however, makes the matching process sensitive to translational motion. The special nature of MRI/CT X-ray images, which is black background with one or more gray object, allows us to design a system that is more robust against translation. The user is allowed to re-align the center of gravity of query image. First we calculate the center of gravity of the image. If the center of gravity is not identical to the center of the image, it is shifted to the center of the image, assuming that the image is extended in all directions with dark background (near zero gray scale value). This operation may truncate parts of the objects so the values in every removed raw or column are checked and if any value is greater than spatial threshold the alignment process is stopped and a warning massage is displayed.

2.2 Feature extraction

After the image passes the preprocessing stage, the query image is ready for generating the feature vector that will be used in the matching process. This vector is generated from the wavelet transform of the image. The 5-layer Daubechies wavelet transform is applied to the image. The output of the wavelet transformation is a 256×256 matrix. The upper-left 16×16 sub-matrix is the fifth layer in the Daubechies discrete wavelet transform [6-7]. This 16×16 sub-matrix consists of four 8×8 sub-matrices. The feature vector is generated in two parts from these four 8×8 sub-matrices. The first part is the 8×8 sub-matrix in the upper-left corner of transformed image that contains the low frequency bands representing the color layout of the image. The second part is the three 8×8 sub-matrices nearby the 8×8 low frequency band sub-matrix. These three sub-matrices do not represent all image details. However, they contain sufficient information to represent important features within the image. Due to the similarity between the images from MRI, CT and X-ray, the variance of the low frequency 8×8 sub-matrix (upper-left corner sub-matrix) has no significance in distinguishing between these image types. Therefore, it cannot be utilized in the matching process [5].

2.3 Matching Process

The feature vector for a system such as WBIIS, which is a color layout indexing system, has to contain spatial information. In particular, the feature vector consists of three parts. The first part is the global features, which are the standard deviations of the three color-channels of 3×8×8 low frequency band sub-matrices. On the other hand, the second and the third parts are the wavelet coefficients of the 16×16 sub-matrix of the color channel. Given the nature of wavelets, this part contains information about spatial variations. The matching step of WBIIS system gives equal weights for all locations in the image. In medical images, however, small objects or image parts may have high diagnostic values. It is not reasonable to give the matching error in background pixels a weight that is equal to such high diagnostic value object within the image. On the other hand, all the pixels of the objects cannot be given the same weight. Therefore, some small parts may have diagnostic value higher than all other pixels. It is very difficult to design an expert system for automatic detection of the importance of each part of an image. Therefore, we allowed users to determine three levels of importance of image regions. First, the user selects the data regions. Then, he/she selects smaller regions inside the data regions with higher diagnostic value. Finally, he/she selects the most important regions. We use these regions to generate a weight function W(x,y) that holds the weight of every pixel in the image to be used during the matching step. From the average of this weight matrix we generate an 8×8 matrix or a 64-destination vector. In the matching phase, we calculate the weighted Euclidean distance based on the following equation for the first part of the feature vector containing gray layout information as a first estimation,

$$d(I,I') = \sum_{i=0}^{3} \| W \,.*\, D_i - W \,.*\, D'_i \|$$

where d(I,I') is the distance between image I and image I'; W is an 8×8 weight matrix ; D_0, D_1, D_2, and D_3 are the four 8×8 sub-matrices representing the feature vector, and the '.*' operator denotes component-wise product .

In the final matching, we calculate the distance depending on the second part of the matching vector, which contains detail information. Then, we retrieve 30 images with the smallest weight Euclidean distance from the PACS and resample them to 128×128 and display them for the user and allow him/her to make the final decision by selecting the nearest image to the query image. The system displays the selected images in their actual size and retrieves the diagnostic report of these images from the RIS. In addition, the system allows the user to retrieve all images of the same examination and the patient record from the PIS.

3. INTEGRATION WITH PACS

In this section, we provide a strategy for the integration of the proposed medical CBIR system with a medical image library. FS-PACS, the integration of PACS, RIS, and HIS, with worldwide web capability can be considered as a medical image library on the Internet. Researchers provided two prototypes for the design of medical image libraries based on centralized data repository and distributed object computing architecture [2]. In this work, the proposed system is designed based on centralized data repository model. Figure 2 shows the main blocks of the system.

Here, CBIR system serves two different kinds of clients [8]. The first class of clients runs on PACS display workstations. This class of clients requires the system to include CBIR preprocessing module and features extraction module in order to reduce the load on CBIR Server (fat client). The second class of clients require a system design that is based on web technology to reduce the download time (thin client). A web-based client is responsible only for sending the query image and region's priority to the web server and displays the CBIR output. The preprocessing and the feature extraction processes in this case run on the CBIR server. In the normal case, web browsers run on small workstations with a maximum of 256 gray levels. Because of the relatively higher resolution of medical images (up to 16 bit/pixel), they cannot be displayed in their full gray scale resolution on these web browsers. Consequently, the web server is allowed to reduce the color resolution and the size of these images to become more suitable for downloading and displaying on web browsers. The client program is implemented using JAVA.

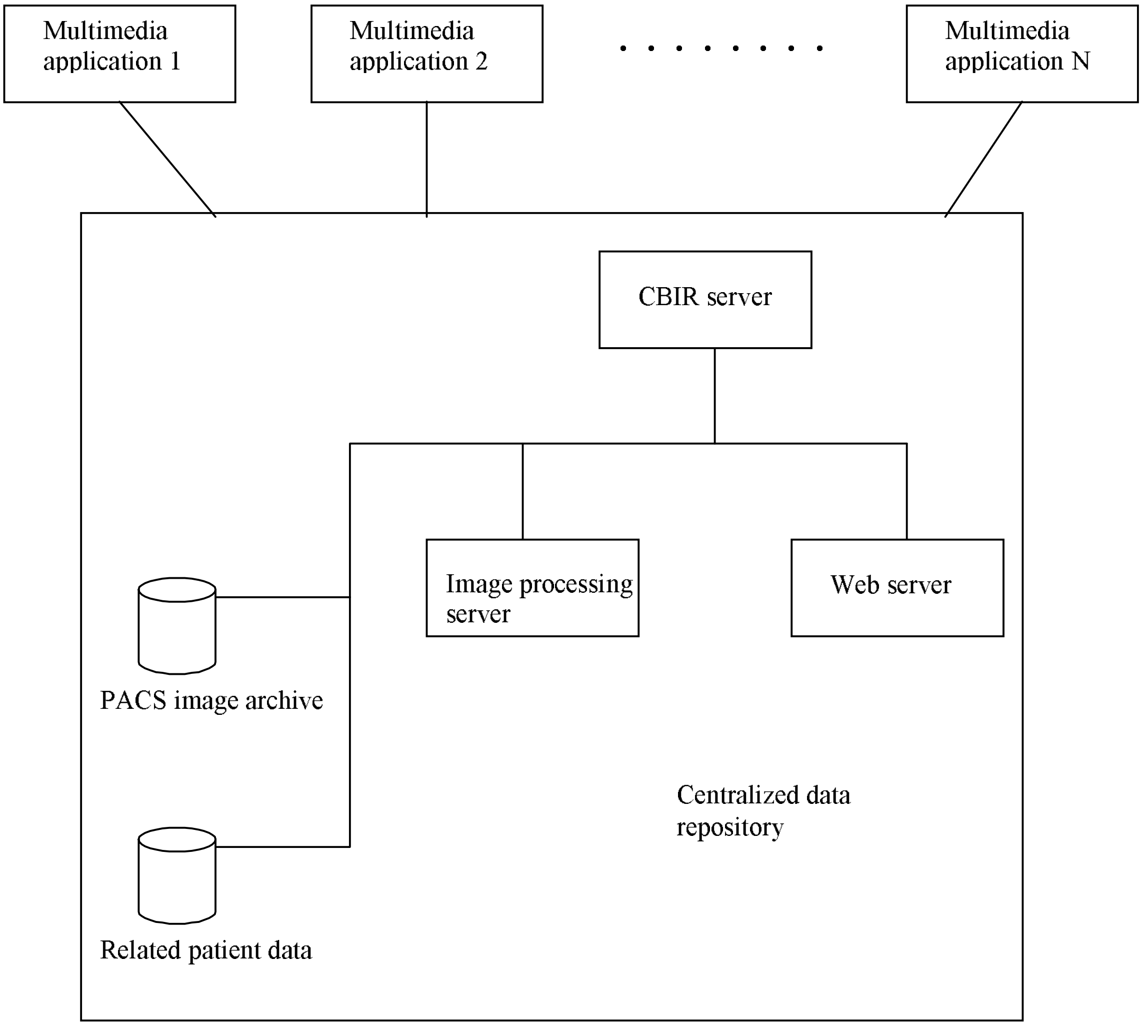

Figure 2: Basic block diagram of the system.

4. IMAGE RETRIEVAL MANEGMENT SYSTEM

In general, PACS is designed as a closed system that provides services for a limited number of users. Standard PACS is designed based on centralized data repository architecture since medical image data are usually archived in a simgle large high-performance server. This server provides all medical image retrieval and storage services for different workstations. When the number of users in PACS or the number of retrieval and storage operations increase, the archiving server will be loaded and become a bottleneck in the system. Even when the archiving server uses high performance RAID, the increase in disk operations and amount of transferred data will limit the system performance dramatically. In order to solve this problem, we have two alternatives. The first is to increase the archiving server capability and performance while the second is to reduce the number of disk operations done on archiving server. Increasing the archiving server capability and performance is rather expansive and limited by the most recent developments in hardware especially in the secondary storage. On the other hand, reducing the number of disk operations depends on PACS software design [8-10].

In this section, we provide a strategy for reducing the number of disk operations in the PACS archiving server. Every medical image in PACS must be stored in the archiving server. That is, every image must be written at least once on the server's secondary storage and there is no way to reduce this number without affecting the integrity and reliability of the medical image data. Meanwhile, there is no restriction to prevent the display workstations from retrieving the medical image data from other workstations having a copy of the requested information. Several copies of images are temporarily stored in acquisition workstations or modalities workstations before the images are transferred to the archiving server. Other temporary copies are created by display workstations. The proposed system uses these temporary copies on the display and acquisition workstations instead of retrieving them from the PACS main archiving server.

The technique can be summarized as follows. First, after any acquisition workstations transfers an image to the main archiving server, it sends its IP and the image ID to an extra-added server that works as the image retrieval management server (IRMS). Then, IRMS stores image ID and workstation IP in its database. Second, when any display workstation needs to retrieve an image, it sends image ID to IRMS. The IRMS replies by sending the IP of the workstation that contains a temporary copy of the requested image. Subsequently, the display workstation retrieves this temporary copy. The image ID and display workstation IP are stored in IRMS database since the display workstation now has a copy of the image.

There are three issues need to be considered when these techniques are designed. The first issue is designing the temporary database space on the different workstations. The second is the IRMS design, while the third is the communication protocol between different workstations and IRMS and between workstation themselves.

4.1. Temporary space design

The design criteria for this part are:

1. The data space that holds the temporary copies must be managed without installing special database engine specially for this purpose. It is expansive to install database engines on every workstation besides the fact that the database engine reduces the performance of the workstations since they are not configured to be archiving servers.
2. In workstations, a secondary storage of suitable size and location must be dedicated for data space.
3. Temporary data spaces are bounded in size and they will become full at some point. Therefore, a mechanism must be devised to replace old image data by new images. Least-recently used strategy (LRU) is employed to keep the most recently used images and delete the least used ones whose space will be used to hold new data.
4. Images in temporary data space must be managed through a database table that contains image ID, image location in data space, image size, and last access time field, which is used by the LRU strategy.
5. The data in IRMS must be updated with every addition and/or deletion operation in the temporary data space.

4.2. IRMS

The design of this part must adhere to the following requirements:

1. The database table of IRMS must reflect the contents of all temporary data spaces in all workstations to maintain the reliability of the system.
2. Many images may have more than one temporary copy on several workstations. Therefore, for a single image ID there may be many workstation IP addresses. When these images are requested, the IRMS should reply with the IP of the workstation that gives optimal (or at least near optimal) solution according to the conditions of network traffic and workstation load. For network traffic, a good (near-optimal) solution can be obtained from a static network map of workstation, sub-net and different network devices. Optimal solutions can only be obtained from dynamic network traffic monitoring.

In our system, we design IRMS with a solution based on static network map. Since the benefit of using dynamic monitoring over using static network map is small compared with the complexity of the dynamic monitoring system.

4.3. Communication protocol

In the proposed system, we deal with interacting distributed objects. Therefore, the system must be based on distributed object technology such as Common Objects Request Broker Architecture (CORBA) and Distributed Component Object Model (DCOM). Another technology that can be considered here is the JAVA Remote Method Invocation (RMI). RMI technology runs only with object implemented in JAVA.

5. IMPLEMENTATION

The proposed medical CBIR and image retrieval management systems have been successfully implemented in JAVA programming language. In order to gain the advantage of its platform independence, security, and web programming feature. The JAVA remote method invocation was used for implementing distributed object CBIR system and IRMS are integrated with a PACS of a large teaching hospital based on an ATM network and Oracle 8 database servers.

6. CONCLUSIONS

A CBIR system is implemented and integrated with a PACS system. The new system allows the user to retrieve the images most similar to a certain query image in an efficient manner along with their associated medical reports. The proposed system has the potential of enhancing the diagnostic accuracy of radiographic examinations.

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