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Relevance Feedback and Intelligent Technologies in Content-based Image Retrieval System for Medical Applications

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Abstract

Relevance feedback has gained much interest from researchers in the discipline of content-based image retrieval (CBIR). However, such approach is rarely used in the content-based medical image retrieval (CBMIR) systems. This paper reviews current CBMIR systems and discusses the possible applications of relevance feedback and intelligent technologies in the perspective areas of research for these systems. As a pilot study, this paper paves the ground work and provides a starting point of future research.

1 Introduction

Over the last few years, images have become one of the most popular ways of storing information. In some situations, it is a better alternative than text-based documents for capturing and representing the information. With the introduction of digital cameras, scanners, world-wide-web (WWW) and cheap data storage, the amount of information in image format has grown exponentially. While this presents a wealth of information, however, it also causes a great problem in retrieving appropriate and relevant information during searching. This has resulted in the growing interest in content-based image retrieval (CBIR) system.

One of the active areas of research in CBIR is the use of different approaches in bridging the gap, semantically and visually, between queries constructed by users and the target search items. One of the problems for any CBIR systems is the users' inability to construct queries which correctly represent the true intention of their need. Over the past 3 – 5 years, literatures related to this area of research have been growing in a rapid rate, but most of these publications have been aimed at the general domain systems. Only a handful of reports have targeted domain specific image retrieval systems. A content-based medical image retrieval (CBMIR) system is typical example of a domain-specific retrieval system.

During the past two decades, the development of new modalities such as Computed Tomography (CT), Magnetic Resonance Imagining (MRI), and Picture Archiving and Communication Systems (PACS) have resulted in an explosive growth in the number of images stored in databases. Until recently, textual index entries are mandatory to retrieve medical images from a hospital image archive system. However, the development of CBIR techniques has not only created new possible ways of retrieving images, but also opened out opportunities for other related applications.

It is however simplistic to consider that one can directly apply a generic CBIR system to a medical image database. In fact, many have regarded medical images as a unique field which poses its special characteristics which have attracted attention from many researchers.

In this study, it is intended to introduce to the readers the characteristics and the development trend of CBMIR systems from the perspective of one whose background is of CBIR systems. In particular, attention will be focused on the applications of relevance feedback and intelligent technologies such as neural networks for medical image databases. The paper will begin with a discussion on the characteristics of medical image databases, the applications of CBMIR systems and the overall framework of such systems. The paper will be followed by an in-depth discussion on the applications of relevance feedback on CBMIR systems. Applications of intelligent technologies will also be touched upon. Finally, the paper concludes by summarising the development trend of CBMIR systems and how relevance feedback may be applied.

2 Characteristics of Medical Image Database

First of all, three characteristics of medical image database are identified. Each of these characteristics of the system presents a different challenge to the research community.

The following sub-sections provide a more detailed discussion on the characters of the CBMIR systems.

2.1 Heterogeneity

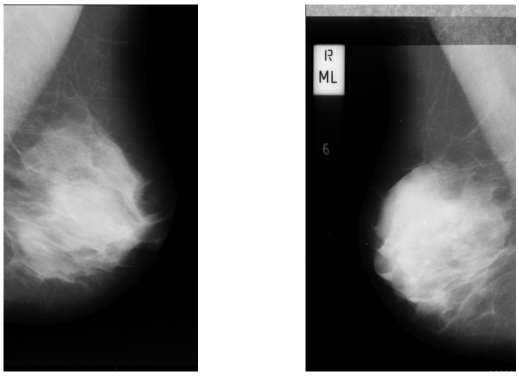
Medical image is only a general phrase and used by many to describe images which captured information about the human body. It is actually a broad discipline that consists of image classes such as photography (e.g., endoscopy, histology, dermatology), radiographic (e.g., x-rays), and tomography (e.g., CT, MRI, ultrasound). It imposes unique, image-dependent restrictions on the nature of features available for abstraction. Each of the image classes possesses its unique characteristics in terms of size, shape, colors and texture of the region of interest. Thus, the visual appearance of the same organ or part of the human body will be interpreted differently under different modalities. Furthermore, it is also possible that the interest in the same image may depend on different users or systems and for different applications. Thus, it is not difficult to deduce that appropriate approaches will be required for different modalities, systems and application. These approaches may include the change of design of user interfaces, indexing structures, feature extraction and query processing units for diverse applications.

2.2 Imprecision

Imprecision has been a problem for the CBIR systems. Likewise, CBMIR systems suffer the same problem. Tagare et al. [20] have identified three components in imprecision, i.e., semantic imprecision, feature imprecision, and signal imprecision. *Semantic imprecision* is the inability to precisely articulate medical concepts via medical terms. This is sometime due to the use of non-standardized dictionary in the medical profession, or quite possibly, the use of same term but under different context.

Feature imprecision is the inability of agreeing the observation of an image by different observers. It is quite common for different medical experts to have different opinion about a case based on their areas of expertise and experience. Thus, the retrieval of images base on the image semantic content becomes relatively subjective.

Lastly, *signal imprecision* is related to the quality of information captured by the image. It is important to point out that in this case it may not be caused by the quality or the resolution of the image, but more than likely, it is due to the nature of the information captured. Quite often, it is rather difficulty for the system to automatically identify the boundary of the object of interest. For instance, mammograms as shown in Figure 1 are often difficult to identify the boundary of the breast, a special approach has to be applied [2] for extracting the shape feature of the breast.



(a) (b)

Figure 1: Two mammograms obtained from MIAS [24] database. Both images show that the boundaries of the breasts are not clearly defined.

2.3 Dynamism of Indexing Structure

As described in the previous section, the human interpretation of a medical image may vary from person to person. The interpretation of an image from the same person may also change as the person gains more experience. Thus, the area of interest for the same image may change as the interpretation of the image changes. For systems that index images by their semantic contents or the visual features of the area of interest, such changes may result in a need to modify the indexing structure in order to adapt to the user's knowledge. However, traditional indexing structures reported so far are static. The process of re-organizing the indexing structure is mostly manual driven. Hence, a significant overhead is included. Ideally, the indexing structure for medical images should be dynamic while keeping the overhead for re-organizing the indexing structure to minimal. Preferably, very little manual interaction should be required.

3 Applications

Medical imagery is an exciting field for researchers of CBIR. It not only contains vast amount of image resources that the researchers can work on, it also provides practical applications that research theories can be applied to. Due to these reasons, there has been a steady growth in developing medical applications with the use of CBIR techniques. The CBMIR systems are grouped into two categories mostly according to their input data format and to a certain extent, the domain scope of their applications.

Traditionally, there are two standard approaches in querying the system, namely, *query by keywords* or *image examples*. In query by example, diagnostic system is one of the applications where many researchers have been focusing on. As the name implies, the output from these systems is the diagnostic result derives from the system's input image. Until now, the systems reported have only been designed to support specific medical tasks such as retrieval of tumour shapes in mammograms [5], identification of lung disease from computed tomography [16], differentiation of Mantle Cell Lymphoma (MCL) from Chronic Lymphocytic Leukaemia (CLL) or Follicular Center Cell Lymphoma (FCC) using pathology images [3], and retrieving of spine in the x-ray database [10]. All these systems are designed to query by image. The region of interest for the input image is partially or automatically selected by the system. Manual interaction is required when the image resolution is low, or with an inability of applying image models to capture the visual features in interest. It is worth noting that some authors are quite cautious in using the term "diagnostic" for their proposed systems. Instead, these authors prefer to call them decision support system.

In addition to the computer aided diagnostic systems, Liu et al. [9] have developed a teaching assistant system for tomographic images for lung diseases. This system allows the professor to select images with similar texture but may be not belonging to the same disease. The objective is to teach interns to learn how to distinguish various disease images with similar texture.

Currently, the tradition picture and archiving image system (PACS) is used for searching medical images in many hospital or clinical systems. The images stored in the PACS system are normally organized according to their semantic content, or by patient's details, or, other related information. Systems that allow the users to retrieve images via the patient's details and other related information are normally based on the patients' history. Over the past few years, researchers have began to take a closer look at the possibility of applying CBIR to the more traditional clinical image systems such as the PACS. The main goal behind these research efforts is to develop a system which can semi/automatically and accurately retrieve and classify images according to their visual or even semantic content. To our knowledge, most of the researches are still in proposal stage, only a few systems are partially implemented [8, 12, 13].

4 Architecture Overview

4.1 Overall Framework

The PACS systems discussed in the previous sections are rather simple as a content-based image retrieval system. At the minimum, a CBIR should consist of components as depicted in **Figure 2**. Clearly, the PACS systems lack the system module for feature selection, and quite possibly the images are indexed by a very simple one-dimensional structure grouped by the label given to the images.

Diagnostic systems reported so far are only designed for very specific application. It may not be possible for such systems to transfer to other medical applications. The reason is obvious, different diagnostic system uses different visual features for identifying different medical cases. Thus, the feature extraction approach for each system will be different. Often, such systems are also static, implying that a significant overheard is required for a visual feature to be added, deleted or modified. Furthermore, the indexing structure applied for these systems are often not targeted for a large database and definitely not for image browsing.

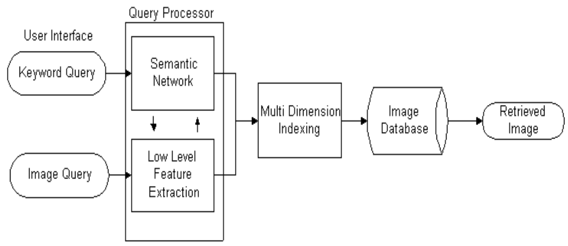


Figure 2: A possible framework for CBIR

Tagare et al. [20] have identified several necessities for CBMIR systems: (a) non-textual indexing, (b) customized scheme, (c) dynamic modules, (d) similarity modules, (e) comparison modules, (f) iconic queries, (g) descriptive language, (h) multi-modality registration, (i) image manipulation. Researchers have generally viewed these necessities as the guideline for building a more complete CBMIR system.

The system proposed by Mojsilovic and Gomes [12] is one of the first systems reported for attempting to build an integrated system for medical image indexing and browsing. The system categorized the images by identifying different perceptual characteristics of different medical modalities. Different image processing techniques were then applied to extract visual features such as colour composition, texture, shape and etc for identifying different modalities.

Lehmann et al. [8] have proposed an image classification framework called Image Retrieval in Medical Application (IRMA). This framework has the potential of answering every system requirements as listed by Tagare et al [20]. IRMA is a multi-layer framework that provides separate layers which include: identification of image categories, extraction of image content and local features, indexing images based on their semantic content and image retrieval on the semantic level.

4.2 CBIR vs CBMIR

One of the major differences between the domain specific framework, such as the IRMA project as mentioned in the previous section, and the more traditional CBIR framework [17] is that this framework uses prior knowledge of different medical modalities to determine the content of the images. Readers should not underestimate such mentality shift. The knowledge applies in the design and implementation of retrieval systems for narrow domain application can prove to be a major difference between the two types of systems. For instance, medGIFT [14], a CBMIR system used in daily clinical routine in the university hospital of Geneva, is an adaptation from the free-of-charge CBIR system GIFT (GNU Image Finding Tool) [18]. The modification was mainly made in the colour model used in processing the images. The modified system reduced the number of colours while increased the number of grey levels to accommodate for the predominantly greyscale medical images. This small change resulted in a better retrieval result and it is only possible with the prior knowledge about the images in the database.

In most of the generic CBIR systems, colour is the most common used visual feature used in describing images, and some systems also use simple statistic texture analysis to describe the "smoothness" of an image. It is extremely difficult for these systems to apply the more complex image analysis models, such as shape detection and texture segmentation, to further analyse the images. As for the CBMIR systems, it is quite common for these systems to use texture and shape to perform more abstract analysis such as segmentation of different texture or colour regions and establishing spatial relationship between objects/regions of interest. For example, Liu et al. [9] used Fourier transform to calculate the texture property and spatial relationship between the regions of interest for the classification of different CT images according to the lung diseases.

5 Relevance Feedback

During the last few years, researchers have introduced relevance feedback into image retrieval systems and since then there have been a dramatic increase in literature reporting the applications of relevance feedback in CBIR systems [15]. The reason being the interpretation of an image can be very abstract and the interpretation varies between users of different backgrounds. Relevance feedback provides an elegant approach in bridging the gap that exists between the high level semantics in the human mind and the low level features managed by machines.

In the following sub-sections, a general overview of relevance feedback is provided. The focus of the discussion is not on the techniques developed for relevance feedback. Interest readers should refer to [19, 23] for a comprehensive review on these techniques. Instead, the attention is turned to providing readers with a basic understanding of the methodology and how it can apply to CBIR or more specifically CBMIR framework. This subsequently leads to the use of intelligent technologies for this application.

5.1 Basic Idea of Relevance Feedback

Relevance feedback is a strategy that invites interactive inputs from the user to refine the query for subsequent retrieval. This approach generally starts from prompting users to search the system via keywords, image examples or a combination of both. The system then prompts the user to select the relevant images from the search result. After the user selected the images, the system will refine the original query by analysing the common features among the selected images. This process is continued iteratively until the target is found. The selection of the common features will be most appropriate for the applications of intelligent technologies such as neural network and fuzzy logic. Evolutionary computation techniques could also be used in optimising the process.

5.2 Characteristics of Relevance Feedback

Relevance feedback is an approach designed to learn from the user's behaviour through the feedback and interactive manner. In this proposed study, three characteristics of this approach have been identified. The characteristics are as follow:

- *Small sample data*. Typically, users do not have the patience to iterate through many cycles of retrieval result to fine tune the query. The size of training data is generally small. Hence, the technique used to implement relevance feedback has to be able to handle small set of training data. The singularity issue arises when the number of training examples is smaller than the dimensionality of the feature space.

- *Type of training sample*. Different techniques may require different type of training data, but the techniques can be grouped according to the way sample data is labelled. In general, we can label the data in yes/no fashion, more commonly known as binary data, or rank the data via certain criteria. In binary input, some techniques only require the binary feedback for positive examples. In some other examples, negative examples are also required. As for the ranking feedback, the algorithms are more interested in the degree of relevancy or irrelevancy amount the feedback images. For instance, "image A is more relevant to the target image than image B and C."

- *Real time processing.* For practical reasons, the techniques applied to the analyses of the input images and the feedback result has to be sufficiently fast. This is to allow the user to interact with the machine on real time basis.

6 Applications of Relevance Feedback and Intelligent Technologies in CBMIR

In Section 3, it is observed that the current CBMIR systems are mostly used for education & decision support purposes. Most of these systems do not implement relevance feedback or only uses relevance feedback in a very limited way. For instance, ASSERT system implemented and designed by Shyu et al. [16] only uses one feedback iteration to retrieve the targeted image. In fact, only a few of the applications reported utilise the learning and classification abilities provided by the relevance feedback approach.

In CBIR systems, relevance feedback is often used to narrow the scope of the user's intention. To a certain degree, this is less of an issue for a more define and narrow domain retrieval system such as the decision support systems. However, it is also true that these systems are no way close to satisfying the essential features that are listed by Tagare et al. [20]. Relevance feedback will be a useful compliment to systems with a more dynamic framework such as one proposed by Tagare et al. [20] and Lehmann et al. [8].

The following is a brief discussion on the applications of relevance feedback in different part of the CBIR components as depicted in **Figure 2**. Each sub-section will begin with current trend of the technology in CBMIR systems and followed by a discussion of the possible applications of relevance feedback and intelligent technologies in each of these components.

6.1 Query Processing

Query processing, in any content-based retrieval systems, is a module between the user interface and the indexing structure. It acts as a module to bridge the semantic gap between the user's input and the actual query applied to the database. In shorts, it converts the user input into a feature vector to be applied for searching through the index tree. Thus, the approach applies to this component is tightly coupled with the design of the user interface and the image indexing structure employed by the system. Hence, issues such as polysemy and synonymy associated keyword/s, and the interpretation issue associated with image example, is mostly handled by this module. Natural Language Processing (NLP) coupled with fuzzy logic will be applicable in this stage for initial filtering and processing of the queries.

6.1.1 Query By Keyword

One of the biggest challenges facing researchers in query with keywords is the ability to accurately represent the user input by the system-constructed query. One of the major reasons for the low accuracy of the search result is caused by misrepresentation and misinterpretation by the system in interpreting the user's query. To a large degree, this is caused by the expressive nature of human language. Polysemy (word with multiple meanings), synonymy (different words with same meaning) and context sensitivity of a word or phrase are the primary reasons for the miss-interpretation of user inputs. In a narrow domain, these problems can be partly dealt with by applying techniques such as word dictionary, word stemming or thesaurus to reduce the ambiguity caused by the keywords. However, there are no CBMIR system to our knowledge that allows the user to construct approximate query with phrases such as "looks like", "more red" or more even complex combination query such as "retrieve 5 images that looks 30% like the input image". Clustering and classification will be necessary in here to identify the keywords and build up the profiles. Semantic relationships of the keywords can also be expressed in tree structure and used for decision making and fuzzy techniques could again be applied.

6.1.2 Query By Image

In recent years, with the advancement of image processing techniques, query by image example has emerged as a popular option for constructing searches in CBMIR systems. Reason being, query by image example can avoid the ambiguity issue surrounding with keyword query. Some systems also provide options for user to specify the relative importance of each feature in the image, or functional features to let the user to manipulate the input image. All these extra options are designed for constructing queries that have a better representation of users' intention.

In query by image example, the query is constructed by extracting the relevant features from the input image and a search vector that uses these features. Weights can also be assigned to fine tune the importance of each element in the feature vector. Depending on the application, the weights of the feature vector can be explicitly assigned by users, or assigned by system through a system defined rule or relevance feedback from the user. The use of evolutionary computation techniques can be applied to find optimal representation of the weights and vectors in order to provide a more accurate search and retrieval.

6.1.3 Relevance Feedback

In relevance feedback, query ambiguity can be minimised by refining the query through user interaction. In general, there are three ways of refining query:

- *Query Point Movement.* The basic idea of this approach is to move the query point closer to the target and away from the non-relevant examples. This is essentially re-adjusting the distance function for the query point.

- *Re-weighting*. This approach is to cover the target images by increasing the value, i.e. the weight, of the important features while reducing the value of the non-relevant feature. If a vector is used for representing the feature space, then this merely becomes parameter adjustment along the line of independent axis weighting in the feature space.

- *Query expansion*. Such approach can be regarded as a multiple-instances sampling approach. This is mostly done by expanding the query to cover the neighbour images of the subsequent feedback from the user.

6.2 Feature extraction

Feature extraction is the core feature of any CBIR systems. This module is either directly or indirectly related to all the different components in a CBIR system. In fact, the selection of the indexing structure and design of the query processing unit is directly affected by this module.

Comparing to the general domain retrieval system, the features selection process for the current CBMIR systems tends to be straightforward. Domain specific applications such as diagnostic systems [5, 10, 16] can apply their domain knowledge to assist the selection of important features required in identifying the disease, tumour or condition that the specialist is interested in. Mojsilovic and Gomes [12] also use the knowledge of the visual feature of each modality to group the collected images. The process of determining features for these applications is mostly manual driven. Clearly, this is not acceptable if the system is to be more dynamic.

Again, relevance feedback can be used to "learn" about the important features exist among the return images selected by the user as "relevant" or "non-relevant". The IRMA framework [7, 8] is using relevance feedback together with the region of interest approach to analyse the common features exist among the class of images. More importantly, such approach provides the ability to classify the images according to the user's personal interpretation.

Over the last few years, relevance feedback has evolved from simple heuristic based weight adjustment techniques to become a clustering problem. The perception is to focus more on the feature/s that can cluster the positive examples. For instance, MacArthur et al. [11] used a relevance feedback decision tree to learn the most common features present in the query image and images gathered from the user's positive feedback together as a class. In their experiment, they have successfully classified the high resolution computed-tomography (HCRT) greyscale images of human lungs into different groups of lung diseases.

As for the more advance techniques, Tieu and Viola [21] used more than 45,000 visual features and a boosting technique to learn a classification function in this feature space. These features were argued to be expressive for high-level semantic concepts. In addition, Laaksonen et al. [6] have constructed a tree-structured self-organizing map (TS-SOM) to dynamically cluster the data during relevance feedback. They have used TS-SOMs to index the images along different feature axes. This approach requires the positive and negative examples to be mapped on to positive and negative impulses on the map and a low-pass operation is used to analyse and extract features with high discriminatory power.

One can also treat the feature selection process as a statistic estimation problem. Over the last few years, Bayesian learning [4, 22] has been one of the most prominent and promising techniques applied to relevance feedback. The basic idea of such learning algorithm is to use the feedback cycle to estimate the important common image features select by the users, and predict the appropriate class/es of images for the next retrieval cycle. Alternatively, Najjar et al. [15] treated the feature extraction process as a probability density problem. Their feature selection process is based on the mixture models and the expectation maximisation (EM) algorithm. In their approach, the EM algorithm is used in estimating the probability density component of the mixture model.

Interest readers can refer to reference [23] for a comprehensive review on the different relevance feedback techniques applied in image feature classification. There are certainly plenty rooms for further research on the intelligent classification techniques being applied in this area.

6.3 Indexing Structure

In order to make any CBIR systems truly scalable for large size image collection, the images are required to be indexed in a systematic manner. In a traditional database system, the data is indexed by a search key or combination of keys that uniquely identify an individual record. Often, a simple one dimensional data structure is adequate for indexing the data in such systems. However, images are more complex. Attempts to reflect this complexity usually results in images being represented by a set of values or attributes, commonly known as the feature vector. When images are represented in this manner, each value in the set becomes a point in an n-dimensional space, implying a multi-dimensional structure is required.

So far, the research efforts for indexing structures applied to CBMIR systems have been mostly revolved around two issues, and they are:

1. What data to be indexed?

2. How is the data organized?

These two issues are rather common in database and data structure communities. However, with the complexity of images and the high dimensionality of the visual features, the answers to these two questions may not be as trivial as it is for the traditional text database systems. Again, intelligent technologies should be explored to provide a more effective means to access and manage the database through more efficient indexing structures.

6.3.1 Indexing Value

The previous section has discussed the possible visual features that can be used in indexing the image databases. However, visual features are only one of the possible features that can be used for indexing images. Depending on the application, image index structure can also be grouped by keywords, which is a great tool for capturing the semantic content of the images. In some cases, the image database may be better represented with the combination of semantic and visual features.

Su and Zhang [19] have proposed a relevance feedback framework that allows images to be indexed by visual features and semantic keywords. The main difference between the normal and relevance feedback framework is that the later framework allows user to label the images through an interactive feedback manner. An advantage of this approach is to utilise the learning capability of the feedback framework to semi-automatically classify the related images, visually and semantically, into the same group.

6.4 Structure

Indexing structure has been a key research topic for researchers during the past years. This is mostly because it is essential to have a fast and efficient indexing structure in order for the database system to be scalable. As for CBMIR systems, many researchers have added two addition requirements to the system's indexing structure. The indexing structure has to be multi-dimensional and dynamic.

Multi-dimensional index is a structure that is often used in indexing large and complex data. These data include audios, videos, images and etc. Indexing tree is the most common used indexing structure for image database, and there are different types of indexing trees designed to accommodate different query requirements. Reader can refer to reference [1] for a comprehensive review on the difference tree-based indexes available for image data.

One of the issues in applying indexing tree is the dimensionality of the index. The performance of the multi-dimensional indexing structure such as popular R-tree and R*-tree degenerates drastically with an increase in the dimensionality of the underlying feature space, this is mostly because the trees' fan-out decreases in inversely proportional to the dimensionality. To solve this problem, one promising approach is to reduce the dimensionality of the feature vector by clustering similar features together to perform recognition or grouping. As discussed in Section 6.2, this can also be achieved via relevance feedback and appropriate intelligent techniques.

7 Conclusion and Future Development

This paper has discussed the major components in the CBMIR systems and the applications of relevance feedback and intelligent technologies. In this study, it was found that relevance feedback strategy is rarely used in any of the CBMIR systems that were reviewed. This should not be a surprise as the relevance feedback is generally used in applications where the domain scope is not clearly defined. The systems reported are only for diagnostic, decision support or teaching purpose. The application for these systems is very specific. Hence, relevance feedback is not required for bridging the gap between the user and the system. However, one can foresee that relevance feedback approach will become more popular among the CBMIR systems when the systems move toward a more integrated and dynamic framework as proposed by previously Tagare et al. [20] and Lehmann et al. [8]. Furthermore, encouraging results have already been reported in [11, 15]. This paper forms part of an initial finding in the background study of a research project and it is expected results from further work will be reported in the near future. The aims of our research are:

7.1 Integrated Framework

To most of the users, they are not trained to browse or search images by simply using the low level visual features of the target image/s. Similarly, it is extremely difficult to represent different classes of images by using simple text labelling system. Thus, we believe it is necessary to combine both the semantic and visual features together for a more meaningful representation of the image collections.

Figure 3 shows the framework of the CBIR system which we aim to implement. It is an extension of **Figure 2** which is the framework originally developed by Su and Zhang [19]. In the original framework, the system supports both query by keyword and query by image example through semantic network and low-level feature indexing. In addition to the semantic search, this annotation propagation process also allows the retrieval system to accumulate users' feedback information such that images with the same semantic content can be labelled and grouped. However, the original framework does not support the multi-levels feature processing. The same set of visual features is used through out the entire image collection, as the result certain groups of images may be represented by inappropriate set of features. Hence, one of our goals is to provide significant enhancements allowing feature customisation for different groups of images and according to requirements from the users.

7.2 Intelligent Framework

As stated in the previous section, we also believe there is no single image model that can be used to capture the important features of all the different medical modalities. Different modality has to be represented by different image model. However, with the use of the learning ability of relevance feedback together with intelligent techniques, it is possible to develop a framework that can automatically select the appropriate model for representing different modality. Thus, the second goal of this project is to develop a semi-supervised framework which has the ability to manage and select the most appropriate image model/s for representing and capturing the important features of each individual different class of images. This is to say each individual class will be represented by the image model/s most appropriate to them. Consequently, the criteria for the selection of the image model/s are also going to an area of interest for this research study.

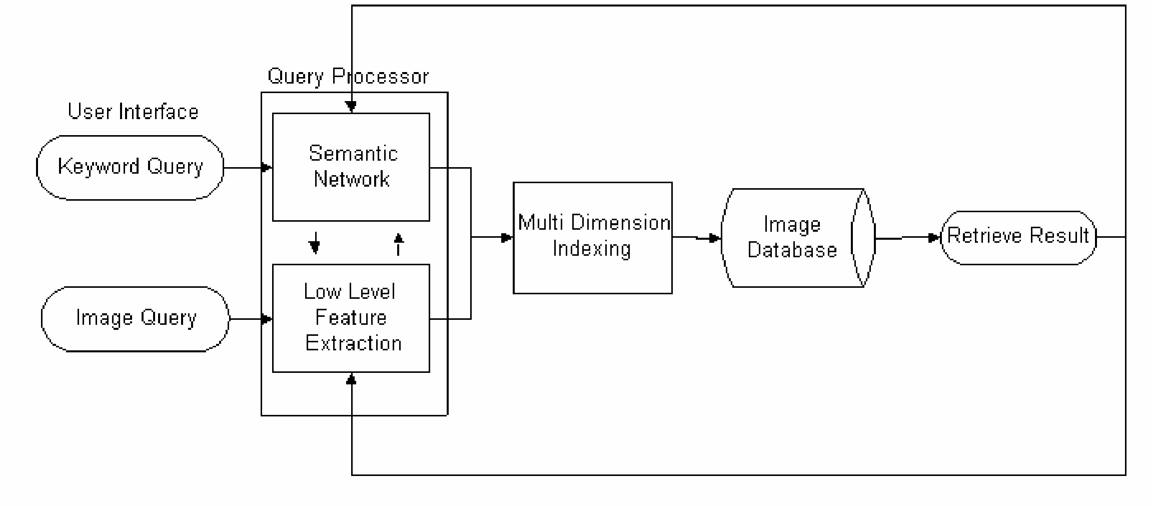


Figure 3: A proposed relevance feedback framework for CBIR systems

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