

Explicit Study on Procedures on Content-Based Image Retrieval in Medical Imaging

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Abstract—the advancement in the field of medical imaging system has lead industries to conceptualize a complete automated system for the medical procedures, diagnosis, treatment and prediction. The success of such system largely depends upon the robustness, accuracy and speed of the retrieval systems. Content based image retrieval (CBIR) system is valuable in medical systems as it provides retrieval of the images from the large dataset based on similarities. There is a continuous research in the area of CBIR systems typically for medical images, which provides a successive algorithm development for achieving generalized methodologies, which could be widely used. The aim of this paper is to discuss the various techniques, the assumptions and its scope suggested by various researchers and setup a further roadmap of the research in the field of CBIR system for medical image database. This is a novel approach to provide a typical insight to the prospective researchers, which is unique of its kind.

Index Terms—Digital Images, Medical Imaging, Cbir,

I. INTRODUCTION

Content-based image retrieval (CBIR) is the application of computer vision techniques to the problem of digital image search in large databases. CBIR enables to retrieve the images from the databases [1, 2]. Medical images are usually fused, subject to high inconsistency and composed of different minor structures. So there is a necessity for feature extraction and classification of images for easy and efficient retrieval [3]. CBIR is an automatic retrieval of images generally based on some particular properties such as color Composition, shape and texture [4, 5]. Every day large volumes of different types of medical images such as dental, endoscopy, skull, MRI, ultrasound, radiology are produced in various hospitals as well as in various medical centres [6]. Medical image retrieval has many significant applications especially in medical diagnosis, education and research fields. Medical image retrieval for diagnostic purposes is important because the historical images of different patients in medical centres have valuable information for the upcoming diagnosis with a system which retrieves similar cases, make more accurate diagnosis and decide on appropriate treatment. The term content based image retrieval was seen in literature first time by Kato[7], while describing his experiment of image retrieval of images form a database on the basis of color and shape features. There is a significant amount of growing images databases in medical field images. It is a proven though that for supporting clinical decision making the integration of content based access method into Picture Archiving and Communication Systems (PACS) will be a mandatory need [8]. In most biomedical disciplines, digital image data is rapidly expanding in quantity and heterogeneity, and there is an increasing trend towards the formation of archives adequate to support diagnostics and preventive medicine. Exploration, exploitation, and consolidation of the immense image collections require tools to access structurally different data for research, diagnostics and teaching. Currently, image data is linked to textual descriptions, and data access is provided only via these textual additives. There are virtually no tools available to access medical images directly by their content or to cope with their structural differences. Therefore, visual based (i.e. content-based) indexing and retrieval based on information contained in the pixel data of biomedical images is expected to have a great impact on biomedical image databases. However, existing systems for content-based image retrieval (CBIR) are not applicable to the biomedical imagery special needs, and novel methodologies are urgently needed. Content-based image retrieval (CBIR) has received significant attention in the literature as a promising technique to facilitate improved image management in PACS system [9, 10]. The Image Retrieval for Medical Applications (IRMA) project [10,11] aims to provide visually rich image management through CBIR techniques applied to medical images using intensity distribution and texture measures taken globally over the entire image. This approach permits queries on a heterogeneous image collection and helps in identifying images that are similar with respect to global features. Section 2 highlights about the significance of CBIR in medical imaging followed by methods used for implementation CBIR in Section 3. The recent work done on CBIR is mentioned in Section 4. The issues or research gap from prior work is illustrated in Section 5 followed conclusion in Section 6.

II. SIGNIFICANCE OF CBIR IN MEDICAL IMAGING

There are several reasons why there is a need for additional, alternative image retrieval methods apart from the steadily growing rate of image production. It is important to explain these needs and to discuss possible technical and methodological improvements and the resulting clinical benefits. The goals of medical information systems have often been defined to deliver the needed information at the right time, the right place to the right persons in order to improve the quality and efficiency of care processes [12]. Such a goal will most likely need more than a query by patient name, series ID or study ID for images. For the clinical decision making process it can be beneficial or even important to find other images of the same modality, the same anatomic region of the same disease. Although part of this information is normally contained in the DICOM headers and many imaging devices are DICOM compliant at this time, there are still some problems. DICOM headers have proven to contain a fairly high rate of errors, for example for the field anatomical region, error rates of 16% have been reported [13]. This can hinder the correct retrieval of all wanted images. Clinical decision support techniques such as case based reasoning [14] or evidence based medicine [15,16] can even produce a stronger need to retrieve images that can be valuable for supporting certain diagnoses. It could even be imagined to have Image Based Reasoning (IBR) as a new discipline for diagnostic aid. Decision support systems in radiology [17] and computer aided diagnostics for radiological practice as demonstrated at the RSNA (Radiological Society of North America) [18] are on the rise and create a need for powerful data and metadata management and retrieval. The general clinical benefit of imaging system has also already been demonstrated in [19]. In [20] an initiative is described to identify important tasks for medical imaging based on their possible clinical benefits. It needs to be stated that the purely visual image queries as they are executed in the computer vision domain will most likely not be able to ever replace text based methods as there will always be queries for all images of a certain patient, but they have the potential to be a very good complement to text based search based on their characteristics. Still, the problems and advantages of the technology have to be stressed to obtain acceptance and use of visual and text based access methods up to their full potential. A scenario for hybrid, textual and visual queries is proposed in the CBIR system [21]. Besides diagnostics, teaching and research especially are expected to improve through the use of visual access methods as visually interesting images can be chosen and can actually be found in the existing large repositories. The inclusion of visual features into medical studies is another interesting point for several medical research domains. Visual features do not only allow the retrieval of cases with patients having similar diagnoses but also cases with visual similarity but different diagnoses. In teaching it can help lecturers as well as students to browse educational image repositories and visually inspect the results found. This can be the case for navigating in image atlases. It can also be used to cross correlate visual and textual features of the images.

III. METHODS USED FOR IMPLEMENTING CBIR

Content-based image retrieval hinges on the ability of the algorithms to extract pertinent image features and organize them in a way that represents the image content. Additionally, the algorithms should be able to quantify the similarity between the query visual and the database candidate for the image content as perceived by the viewer. Thus, there is a systemic component to CBIR and a more challenging semantic component.

- **Shape Based Method:** For shape based image retrieval, the image feature extracted is usually an N dimensional feature vector which can be regarded as a point in a N dimensional space. Once images are indexed into the database using the extracted feature vectors, the retrieval of images is essentially the determination of similarity between the query image and the target images in database, which is essentially the determination of distance between the feature vectors representing the images. The desirable distance measure should reflect human perception. Various similarity measures have been exploited in image retrieval. In our implementation we have used Euclidean distance for similarity measurement.
- **Texture Based Method:** Texture measures have an even larger variety than color measures. Some common measures for capturing the texture of images are wavelets and Gabor filters where Gabor filters perform better and correspond well to. The texture measures try to capture the characteristics of images or image parts with respect to changes in certain directions and scale of changes. This is most useful for regions or images with homogeneous texture.
- **Continuous Feature Selection Method:** This method deals with the “dimensionality curse” and the semantic gap problem. The method applies statistical association rule mining to relate low-level features with high-level specialist’s knowledge about the image, in order to reduce the semantic gap existing between the image representation and interpretation. These rules are employed to weigh the features according to their relevance. The dimensionality reduction is performed by discarding the irrelevant features (the ones whose weight are null). The obtained weights are used to calculate the similarity between the images during the content-based searching. Experiments performed show that the proposed method improves the query precision up to 38%. Moreover, the method is efficient, since the complexity of the query processing decreases along the dimensionality reduction of the feature vector.
- **With Automatically Extracted MeSH Terms:** There is still a semantic gap between the low-level visual features(textures, colors) automatically extracted and the high level concepts that users normally search for (tumors, abnormal tissue)[22]. Proposed solutions to bridge this semantic gap are the connection of visual features to known textual labels of the images

[23] or the training of a classifier based on known class labels and the use of the classifier on unknown cases [24]. Combinations of textual and visual features for medical image retrieval have as of yet rarely been applied, although medical images in the electronic patient record or case databases basically always do have text attached to them. The complementary nature of text and visual image features for retrieval promises to lead to good retrieval results.

- Using Low-Level Visual Features and The image retrieval process consists of two main phases: preprocessing phase and retrieval phase. Both phases are described as follows. The pre-processing phase is composed of two main components: a feature extraction model and a classification model. The input of the pre-processing phase is the original image database, i.e. images from the ImageCLEFmed collection, with more than 66,000 medical images. The output of the pre-processing phase is an index relating each image to its modality and a feature database.

- The Feature Extraction Model: The feature extraction model operates on the image database to produce two kinds of features: histogram features and metafeatures. Histogram features are used to build the feature database, which is used in the retrieval phase to rank similar images. Metafeatures are a set of histogram descriptors, which are used as the input to the classification model to be described later. Histogram features used in this system are:

- Gray scale and color histogram (Gray and RGB)
- Local Binary Partition histogram (LBP)
- Tamura texture histogram (Tamura)
- Sobel histogram (Sobel)
- Invariant feature histogram (Invariant) Meta features are calculated from histogram features in order to reduce the dimensionality. These metafeatures are the four moments of the moment generating function (mean, deviation, skewness and kurtosis) and the entropy of the histogram. Each histogram has five associated metafeatures, meaning a total of 30 meta-features with information of color, texture, edges and invariants.

IV. RECENT WORK IN CBIR

Support vector machines (SVM) are extensively used to learn from relevance feedback due to their capability of effectively tackling the above difficulties. However, the performances of SVM depend on the tuning of a number of parameters. It is a different approach based on the nearest neighbor paradigm. Each image is ranked according to a relevance score depending on nearest neighbor distances. This approach allows recalling a higher percentage of images with respect to SVM-based techniques [25] there after quotient space granularity computing theory into image retrieval field, clarify the granularity thinking in image retrieval, and a novel image retrieval method is imported. Firstly, aiming at the Different behaviors under different granularities, obtain color features under different granularities, achieve different quotient spaces; secondly, do the attribute combination to the obtained quotient spaces according to the quotient space granularity combination principle; and then realize image retrieval using the combined attribute function.[26] Then a combination of three feature extraction methods namely color, texture, and edge histogram descriptor is reviewed. There is a provision to add new features in future for better retrieval efficiency. Any combination of these methods, which is more appropriate for the application, can be used for retrieval. This is provided through User Interface (UI) in the form of relevance feedback. The image properties analyzed in this work are by using computer vision and image processing algorithms.

1. Evaluating an emotional response to color images. It is mainly used for the case – base reasoning methodology, emotional evolution of color images values , and also find out fuzzy similarity relational & inter and intra similarities and used for MPEG -7 visual descriptors. [27]
2. 3D Object: The 3D objects make their efficient retrieval technology highly desired. Intelligent query methodology, multiple view and representative query view. [28]
3. Relevance Feedback: Another methodology is classify the query in text or images to relevance / irrelevance set of images to select the positive images. Reference to retrieve the relevance images from databases. [29]

V. RESEARCH GAP

There are various areas to work with for the improvement of the content based image retrieval system. It is already been discussed that the existing techniques may be used to improve the quality of image retrieval and the understanding of user intentions. An approach that combines two different approaches to image retrieval, together with active use of context information and interaction has been proposed. The problem of bridging the semantic gap between high level query which is normally in terms of an example image and low level features of an image such as color, texture, shape and object forced to apply techniques to reduce the semantic gap.

One approach to making a fair assessment of the state of the field is by comparing CBIR applications presented in the literature. However, given the large number of research domains that are included in this technology and its sensitivity As shown in table 1, major recent work that has been published are illustrated brief in accordance with the approaches used by each techniques.

Table 1. Survey on recent researches on implementation of CBIR in Medical imaging

| Author | Year | Approach used |
|----------------------------------|------|---|
| Suresh, Shanmugam | 2012 | Perceptual Hash (P-Hash) Algorithm |
| Leila, Fatima | 2012 | 3D CBIR |
| Ashish, Manpreet | 2012 | Fourier Descriptors, Haar Wavelet, Canberra Distance |
| Akila, Uma | 2012 | Trigonometric Function Distance, wavelets |
| Sanjay, Trimbak | 2012 | High Level Feature, Low Level Features |
| ElBagoury, Roushdy | 2012 | Ranking |
| Gupta, Khurana | 2012 | structured local binary Haar pattern, Haar wavelet |
| Killedar, Patil, Borse | 2012 | Gray level co-occurrence matrix, Principal Components Analysis, Support Vector Machine |
| Christiyana, Rajamani, Usha Devi | 2012 | Two Dimensional Gray level Co-occurrence Matrix, one dimensional Gray level Co-occurrence Matrix, |
| Yu, Zhang, Liu, Metaxas | 2012 | Principal Component Analysis |
| Karthikeyan, Aruna | 2012 | K-Means Algorithm, ranking, Edge Histograms, Edge Extraction Method, Sobel |
| Shambharkar, Tirpude | 2012 | Binary partitioning tree, Minkowski difference, Wavelet |
| Shambharkar, Tirpude | 2012 | Binary tree structure, Canny edge detection Mean, Correlation. |
| Suryanarayana Rao Reddy Babu | 2012 | Pyramid-Structured Wavelet Transform Energy Level Algorithm Euclidean Distance Algorithm |
| Singha Hemachandran | 2012 | Wavelet Based Color Histogram Image Retrieval) |
| Khokher Talwar | 2012 | Minkowski-Form distance Euclidean Distance Manhattan distance |
| Shaila Vadivel | 2012 | HSV colorspace Smooth distribution, NBS distance, background complex |

to the nature and content of the data, it is necessary to develop comparison methods that analyze more than the selection of particular techniques and the experimental results presented in the literature. Rather, it may be better to formally describe an idealized CBIR system and identify the shortcomings in the candidate system. These shortcomings have been labeled as “gaps” and extensively discussed in [30]. The concept of the gap is a generalization of the well-known “semantic gap” that refers to the difficulty of capturing high-level imaged content semantics from extracted low-level image features. These gaps have been broadly categorized into four types and defined below:

1. The Content Gap addresses a system’s ability to foster human understanding of concepts from extracted features. In medical applications, it also refers to the extent to which the system adapts to varying modalities, context, and diagnostic protocols.
2. The Feature Gap addresses the extent to which the image features are extracted. This is measured along several dimensions: degree of automation, degree of detail captured along the content axis (object structure), use of multi-scalar techniques, the use of space and (if available) time dimension in image data, and use of all channels on each dimension.
3. The Performance Gap addresses practicalities of system implementation and acceptance. It evaluates system availability, extent of integration into the medical infrastructure, use of feature indexing techniques, and the extent to which the system was evaluated.
4. The Usability Gap measures the richness of available query features and the extent to which they can be combined, available support for comprehending the results returned by the system, and available support for query refinement. Addressing these aspects makes a CBIR system more usable, and may increase its acceptance into the medical (clinical, research, or education) workflow.

VI. CONCLUSION

In this work, most of systems use color and texture features, few systems use shape feature, and still less use layout features. Ontological Visual descriptor used extensively in various areas to improve the performance of the system and to achieve better results in different applications. Its integrates various features perfectly in content based image retrieval system and reflects the user’s subjective requirements, the experiments achieve good performance and demonstrate the efficiency and robustness of system.. This survey also highlighting the significant contributions of content based image & information’s Retrieval field.

The difficulty faced by CBIR methods in making inroads into medical applications can be attributed to a combination of several factors. Some of the leading causes can be categorized according to the “gaps” model presented above.

1. The Content Gap: It is important to consider image content in light of the context of the medical application for which a CBIR system has been optimized. Too often, we find a generic image retrieval model where the goal is to find medical

images that are similar in overall appearance. The critical factor in medical images, however, is the pathology – the primary reason for which the image was taken. This pathology may be expressed in details within the image (e.g., shape of a vertebra or texture and color of a lesion) rather than the entire image (e.g., spine x-ray or cervicographic image). In addition, there may be multiple image modalities that provide the critical information, e.g., histology slides, photographs, etc. In addition to expanding the scope of the CBIR system it is important to also consider analyzing patient histories or physician’s notes for valuable information

2. **The Feature Gap:** Extracted features are used to define the image content. As such, decisions on the types of features, scale(s) at which the features are extracted, and their use individually or in combination determines the extent to which the system “knows” the image and, to a large extent the system capability. It is necessary for the system to support as many types of features as possible and also capture them at several scales. Medical CBIR applications are very sensitive to medical image content. So, developing toolboxes to permit user selection of features may also be very helpful in generalizing the applications and improving acceptance.
3. **The Performance Gap:** Benefits of medical imaging to science and healthcare have led to an explosive growth in the volume (and rate) of acquired medical images. Additionally, clinical protocols determine the acquisition of these images. There is a need for the system response to be meaningful, timely and sensitive to the image acquisition process. These requirements make linear searches of image feature data, very often presented in the literature, impractical and a significant hurdle in the inclusion of CBIR into medical applications.
4. **The Usability Gap:** This gap is rarely addressed during the design and development of CBIR systems. However, it is the one of most concern to the end user of the system and therefore has the greatest potential for affecting the acceptance of a new technology.

An idealized system can be designed to overcome all the above gaps, but still fall short of being accepted into the medical community for lack of (i) useful and clear querying capability; (ii) meaningful and easily understandable responses; and (iii) provision to adapt to user feedback. The opposite is also true to some extent. A technically mediocre, but promising, system may obtain valuable end user feedback, and by technical improvement may increase user acceptance with the application of usability design principles. Other than item (iii), which still needs significant research effort, the usability gap can only be bridged by keeping the end user in mind from early system development, as well as by conducting well designed usability studies with targeted users. In general, a high involvement of the user community in system design and development can significantly improve adoption and acceptance.

The preceding subsections already showed the large variability in techniques that are used for the retrieval of images. Still, several very successful techniques from the image retrieval domain have not been used for medical images as of yet. The entire discussion on relevance feedback that first improved the performance of text retrieval systems and then, 30 years later, of image retrieval systems has not at all been discussed for the medical domain.

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