Medical Image Retrieval Using Fuzzy Connectedness Image Segmentation and Geometric Moments

Amol P. Bhagat and Mohammad Atique

PG Department of Computer Science, Sant Gadge Baba Amravati University, Amravati, India Email: {amol.bhagat84, mohd.atique}@gmail.com

Abstract—In medical imaging DICOM (Digital Imaging and Communications in Medicine) format is the most commonly used format. Various medical imaging sources generate images in this format, which are collected in large database repository [1]. Various modalities of medical images such as CT scan, X- Ray, Ultrasound, Pathology, MRI, Microscopy, etc [2] are used to collect these images. From the analysis of these medical images proper diagnosis of different diseases can provided to the patients. This paper presents an approach for efficient image retrieval of angiograms, ultrasound and x-ray medical images from the huge medical image datasets. This paper presents the proposed fuzzy connectedness image segmentation with geometric moment approach which provides more precise retrieval results with less computational complexity. This paper compares the various techniques for DICOM medical image retrieval and shows that the proposed fuzzy connectedness image segmentation with geometric moments based image feature extraction and image retrieval approach performs better as compared to other approaches. The proposed method produced results with the precision of 95%.

Index Terms—angiograms, DICOM, feature extraction, fuzzy image segmentation, geometric moments, ultrasound, x-ray

I. INTRODUCTION

Various researches are carried out recently for addressing different issues related to efficient medical image indexing [3] and medical image retrieval [4]. Various approaches for indexing [1], [3] and retrieval [5]-[15], [17]-19] of images are proposed in some recent papers. This paper includes the comparison of color based and texture based image retrieval techniques with the proposed fuzzy connectedness image segmentation with geometric moments for retrieval of various medical modality images including angiograms, ultrasound and xray. The comparison is carried out between proposed approach and various image retrieval approaches such as web based medical image retrieval in oracle [20], pattern similarity based medical image retrieval [6], indexing for relevance feedback in image retrieval [3], [8]-[9], entropy based image retrieval [11], similarity based online feature selection [10], entropy based feature selection [13], [14] and localized content based image retrieval [17] based on different parameters. It is found that proposed approach performs better than earlier approaches.

Computer Aided Diagnostic (CAD) systems [15]-[24] use images in the DICOM format, where an image header may contain some necessary information, such as modality, body part examined, patient information, etc. On the other hand, online medical images are generally stored and accessed in common file formats (e.g., JPEG, TIFF, PNG, etc.). Due to a huge size of images in DICOM format, it is not suitable for storage and transmission in a web-based environment. 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. This can obstruct the correct retrieval of all wanted images. Clinical decision support techniques such as case based reasoning or evidence based medicine [15] 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 [15]. Besides diagnostics, teaching and research especially are expected to improve through the use of visual access methods as visually relevant 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.

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 diagnosis processes. Such a goal will most likely need more than a query by patient name. For the clinical decision making process it can be beneficial or

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even important to find other images of the same modality, the same anatomic region of the same disease.

The implementation of web based system for medical image retrieval using Oracle Multimedia features is given in [20], [24]. The system uses Digital Imaging and Communications in Medicine (DICOM) image file format, which contains additional information regarding modality, acquisition device and patient image identification in its header along with raw image data. The DICOM feature was introduced in Oracle Database 10g Release 2. The system is developed by using Oracle 11g multimedia Database, Oracle JDeveloper, JDK 1.6, JMF and JAXP (Java API for XML Parsing). Oracle Multimedia DICOM support includes: ORDDicom object type, DICOM metadata extraction, DICOM conformance validation and DICOM image processing and image compression.

The main goal is to demonstrate the use of the Oracle Multimedia features for image management and retrieval. Implementation is based only on the Oracle provided methods, operators and visual signatures. Six image categories are used for demonstration. Attributes weights are predefined for each image category. The reference of Picture archiving and communication systems (PACS) is also given in [20], [24]. PACS are used in many hospitals, which are basically computer networks for storage, distribution and retrieval of medical image data.

Oracle Multimedia Classes for JSP and Servlets are used for implementing the application. ORDImage object type is used for the manipulation of multimedia data. ORDImageSignature object type is used for contentbased image retrieval. isSimilar(), evaluateScore(), generateSignature() are the methods used for image data manipulation. IMGSimilar() and IMGScore() are the operators for ORDImage() object type. IMGSimilar() operator determines whether or not two images are match. IMGScore() compares the signature of two images and returns the weighted sum of the distances for the visual attributes.

The system supports various image formats. The new Oracle Multimedia object type, ORDDicom, is examined that has been defined to hold DICOM contents, and to implement the methods to manipulate the DICOM content. ORDDIcom object type supports the storage management and manipulation of DICOM format medical images and other data. A Java proxy class, OrdDicom, is also defined. It provides access to the ORDDicom database object through JDBC in a Java application. Using these classes a web page in implemented from which the user can upload DICOM format image in the multimedia database. The DICOM embedded content is extracted in XML metadata document and stored in the database as SYS.XMLType. After the image is uploaded in the database the application has support for parsing the DICOM attributes from the DICOM content (SYS.XMLType) and displaying them in readable format.

An efficient content based medical image retrieval scheme is proposed in [4, 6]. It is based on PAttern for Next generation DAtabase systems (PANDA) framework for pattern representation and management. It involves block based low level feature extraction (intensity and texture contrast) along with spatial coordinates (depends on patient position) from image and then clustering of feature space to form meaningful patterns. An expectation maximization [4]-[6] algorithm is used for clustering feature space. This algorithm is based on iterative approach to automatically determine number of clusters. The similarity between two clusters is estimated as a function of the similarity of both their structures and the measures component. Pattern base is generated to keep information about pattern in compact way. Pattern base contains pattern type (structure schema and measure schema), pattern and class. Large set of radiographic images were used from the Image Retrieval in Medical Applications (IRMA) dataset [4] to carry out experiments.

The idea of Pattern Base which is adopted from PANDA framework is used in [6]. The pattern base contains pattern type, pattern and class. The pattern structure is described by pattern type. A pattern is an instance of the corresponding pattern type and class is a collection of semantically related patterns of the same pattern type. The pattern type can be simple or complex. The pattern type is combination of structure schema (SS) and measure schema (MS). The medical image representation is treated as complex patterns. Each complex pattern consists of set of simple patterns representing clusters of image regions. A novel scheme is proposed for the assessment of the similarity between complex patterns.

There are a few medical open source projects and initiatives such as Open Source Health Care Alliance (OSHCA), Minoru http://www.minorudevelopment.com /en/healthlinks.html and linuxmednews http://www. linuxmednews.com/ [17]. The advantages of open source, the most frequently mentioned for the medical domain being vendor independence through available source code; reduced risk of bankruptcy, direction change of software producer, or data loss when migrating data; reduced total cost of ownership, including maintenance, software adaptation and user training; ease of adapting software for special needs and help through a large user community. The medGIFT project http://www.sim.hcuge .ch /medgift/ uses the GNU Image Finding Tool (GIFT) http://www.gnu.org/software/gift/, based on Viper, image retrieval platform, allowing us to profit from and share in the developments of other users and researchers [18]. The system is adapted to medical images by emphasizing the importance of grey levels and textures, rather than color features best suited to stock photo databases. A web interface shows the diagnoses of retrieved images links casimage and to http://www.casimage.com/, a teaching file system, with a textual description and further images of the case. The open source license makes it accessible to researchers and Medical Diagnostics who cannot afford expensive products and research projects.

Three different classes of queries primitive, logical and abstract [3] are used to retrieve images in content based image retrieval systems. Color, texture and shape feature based queries are called primitive query. Sketch-based and linguistic queries in which the user describes objects or regions in the desired spatial positions and ascribes attributes, such as class label, size, color, and shape properties, to them are called logical queries. The notions of similarities are used in abstract. Logical and abstract queries are sometimes called as semantic queries. Several popular content based image retrieval systems namely OBIC (Query By Image Content), Virage, Photobook, Chabot, VisualSeek, SurfImage and Netra [2] are available for retrieval of images from large image repositories. But these systems cannot be used for retrieval of medical images. When these systems are used with medical images, the feature extraction approaches used in these systems provides unwanted and not more precise results. Therefore this paper focuses on efficient and precise retrieval of medical images.

II. FUZZY CONNECTEDNESS IMAGE SEGMENTATION THEORY

The basics of fuzzy connectedness image segmentation [18]-[20] are described in this section. Consider a 2D image composed of two regions corresponding to two objects O₁ and O₂ as illustrated in Fig. 1, O₂ being the background. O₂ itself may consist of multiple objects which are not of interest in distinguishing [18]-[20] since object of interest is O₁. Determine an affinity relation that assigns to every pair of nearby pixels in the image a value based on the nearness of pixels in space and in intensity (or in features derived from intensities). Affinity represents local "hanging togetherness" of pixels. To every "path" connecting every pair of pixels, such as the solid curve p_{co1} connecting c and o_1 in Fig. 1 a "strength of connectedness" is assigned which is simply the smallest pair wise affinity of pixels along the path. The strength of connectedness between any two pixels such as o₁ and c is simply the strength of the strongest of all paths between o_1 and c. Suppose, p_{co1} shown in Fig. 1 represents the strongest path between o_1 and c. If the affinity is designed properly, then p_{co1} is likely to have a higher strength than the strength of any path such as the dotted curve between c and o_1 that goes outside O_1 .



Figure 1. Illustration of the main ideas behind relative fuzzy connectedness. The membership of any pixel, such as c, in an object is determined based on the strength of connectedness of c with respect to the reference pixels o_1 and o_2 specified in objects O_1 and O_2 . c belongs to that object with respect to whose reference pixel it has the highest strength of connectedness.

According to the fuzzy topology theory, a field $H = \{\eta(p)\}$ can be derived from any digital image by simply normalizing the pixel-intensity value. A fuzzyconnectedness degree can be computed for each pixel p, and this measure refers to the absolute maximum membership value. However, with the aim of image processing, one can extract a fuzzy-connectedness measure with respect to any image pixel a, given the appropriate transform that is applied to each pixel p. For the sake of clarity, such a transformation, which gives rise to the modified field X^a (Equation 1), is given as

$$x^{a}(p) = 1 - |\eta(p) - \eta(a)|$$
 (1)

Pixel a – seed point assumes the maximum value in the modified field, as shown in Fig. 2.



Figure 2. Modified X^a value as a function of the original value (in).

If we define P(q, p) as connected path of points from a pixel q to a pixel p and if the seed point represents and belongs to a structure of interest, it is possible to measure the connectivity (Equation 2) associated with the structure by applying, for every p, the following:

$$C_{x^{a}} = c_{x^{a}}(p) = conn(x^{a}, a, p) = \max_{P(a,p)} [\min_{z \in P(a,p)} X^{a}(z)]$$
(2)

The max is applied to all paths P(a, p) from a to p and thus refers to the optimum path connecting p to the seed point, while the min is applied to all points z along the optimum path P(a, p). Above equation is named " χ -connectivity" or "intensity connectedness," and its application results in an image where every pixel value represents the degree of membership to the searched object. The new image produced is called the "connectivity map," where each image element has a gray level that is dependent on the degree of connectivity with respect to seed point a.

III. EXTRACTING SHAPE FEATURES USING GEOMETRIC MOMENTS

Geometric moments [18]-[20] have proven to be a very efficient tool for image analysis. The various examples of the use of moments are aircraft identification, scene matching, shape analysis, image normalization, character recognition, accurate position detection, color texture recognition, image retrieval and various other image processing tasks.

For a two-dimensional density function p(x, y) the $(p + q)^{th}$ order geometrical moments m_{pq} (Equation 3) are defined as:

$$m_{pq} = \int_{\infty}^{\infty} \int_{\infty}^{\infty} x^p y^q p(x, y) dx dy$$
(3)

If p(x, y) is a piece-wise continuous function and has non-zero values only in the finite part of the x-y plane, then moments of all orders exist for p(x, y), and the moments sequence m_{pq} is uniquely determined by p(x, y)and vice-versa. Although originally described in continuous form, discrete formulae are commonly in use for practical reasons. If an image is considered as a discrete function f(x,y) with $x = 0, 1, \ldots, M$ and y = 0, $1, \ldots, N$ then $(p+q)^{th}$ order geometric moments m_{pq} (Equation 4) are defined as :

$$m_{pq} = \sum_{x=0}^{M} \sum_{y=0}^{N} x^{p} y^{q} f(x, y)$$
(4)

It should be noted that second equation can assume very large values, especially for high order moments (large p, q). This often leads to numerical instabilities as well as high sensitivity to noise [18]-[20]. Furthermore, image reconstruction is not straightforward.

IV. IMAGE RETRIEVAL AND FEATURE EXTRACTION USING PROPOSED FUZZY CONNECTEDNESS IMAGE SEGMENTATION AND GEOMETRIC MOMENTS

Image Segmentation is used to find the (x, y) coordinates of the largest image segment and (x, y) coordinates of the boundary of the largest image segment. Store the information of all consecutive pixels having same discrete level. Determine whether a group of pixels are coherent or not. Get the color and pixel count. After scanning a new line, look for any coherent group of pixels that does not extend to the new line and determine whether they are coherent or incoherent by comparing the pixel count with threshold. Check whether i-th pixel is the boundary of the largest image segment or not. The following algorithms are used for feature extraction and medical image retrieval using proposed fuzzy connectedness image segmentation with geometric moments.

A. Iimage Segmentation Algorithm

Input: Image and Seed point.

Output: Segmented Image.

- 1. Initialization
 - 1.1 Seed point 'a'
 - 1.2 P(q,p) ← path of points from a pixel q to pixel p
- 2. Obtain modified field by normalize the pixel intensity values.
- 3. Pixel 'a' selected as seed point assuming that it has maximum value in the modified field.
- 4. If 'a' represents and belongs to a structure of interest then
 - 4.1 Measure the connectivity associated with the structure by applying
- 5. Return the connectivity map
- 6. Adjust threshold if necessary
- 7. Select best segmented result
- B. Algorithm for Geometric Moments

Input: Query Image

Output: Set of similar images to query image from the set of *N* images

- 1. Initialization
 - 1.1 pValue, qValue ← 1 for second order geometric moment
 - 1.2 size \leftarrow height*width
 - 1.3 Array pixel[size]
 - 1.4 Declare vector geometricMoment
 - 1.5 moment $\leftarrow 0$
- 2. For j = 1 to height do
 2.1 For i = 1 to width do
 2.1.1 If pixels[j*width + i] ==
 foreground then
 2.1.1.1 moment = moment + (iweight[0])^{pValue} * (j-weight
 - [1])^{qValue}
- 3. Add moment to feature vector geometricMoment
- 4. Compare this feature vector with the feature vectors of *N* images stored in the database using distances between them. According to the distances the system returns nearest neighbors as the query result.
- V. EXPERIMENTAL RSULTS AND DISCUSSION FOR VARIOUS MEDICAL IMAGE MODALITIES



Figure 3. Some sample images considered from angiogram (a)-(b), ultrasound (c) and X-ray (d) medical image modalities.

Medical images are daily received in DICOM standard from hospitals [21]-[24]. The DICOM standards committee is responsible for DICOM maintaining an evolving standard in accordance with the procedures. Therefore the angiograms, ultrasound and x-ray images in DICOM formats are considered for carrying out experimentations in the research work. The implemented research work can also process images in other formats. By carrying out the experimentation on angiograms, ultrasound and x-ray image modalities the implemented approach is compared on the basis of feature extraction time, retrieval time, and number of images retrieved. The experimentation has been carried out on the dataset containing more than 15,000 images. For these images 90,000 different features have been calculated. For each type of image different weights have been considered for visual attributes in angiograms, ultrasound and x-ray modalities. The different types of images considered from angiograms, ultrasound and x-ray medical image modalities [21]-[24] are shown in Fig. 3.

The existing color feature based approaches color moments, local color histogram (LCH), global color histogram (GCH) and texture based approach cooccurrence [22]-[24], are compared with the proposed fuzzy connectedness image segmentation with geometric moments. Retrieval time and feature extraction time are used to carry out the comparison among existing and proposed algorithms.

Table I shows the comparison of the implemented algorithms on the basis of feature extraction time (in Seconds) for angiogram, ultrasound and x-ray medical image modalities. From the Table I, it is clear that the

proposed approach is not faster as compared to LCH and co-occurrence, but it gives more precise feature extraction results. The GCH and color moments methods are faster but they do not produce precise results. Table II shows the comparison of the implemented approaches on the basis of image retrieval time (RT) (in Seconds) and number of images retrieved (NIR) for angiogram, ultrasound and x-ray medical image modalities. As proposed approach fuzzy connectedness image segmentation with geometric moments is used for shape analysis initially obtains segments of images and then computes the geometric moments for those segments, in both cases, i.e. feature extraction as well as image retrieval this method required more time as compared to the remaining approaches. It can be observed from the Table II the number of images retrieved by the proposed approach are less as compared to other approaches. After comparison it has been found that the proposed approach produced 95% precise results.

 TABLE I.
 FEATURE EXTRACTION TIME FOR ANGIOGRAMS, ULTRASOUNDS AND X-RAYS IMAGE MODALITIES USING COLOR MOMENTS, CO-OCCURRENCE, LOCAL COLOR HISTOGRAM, GLOBAL COLOR HISTOGRAM AND PROPOSED APPROACH

Medical Images	Feature Extraction Time						
	Color Moments	Co-occurrence	Local Color Histogram	Global Color Histogram	Proposed Approach		
Cerebral Angiogram	369.76	810.43	607.83	217.80	2633.91		
Coronary Angiogram	125.14	274.29	205.71	73.71	891.43		
Brain Ultrasound	91.25	200	150	53.75	650		
Chest X-Ray	2736.22	5997.18	4497.89	1611.74	19490.85		

TABLE II.	NUMBER OF IMAGES RETRIEVED AND IMAGE RETRIEVAL TIME	FOR ANGIOGRAMS, ULTRASOUNDS AND X-RAYS IMAGE MODALITIES
USIN	NG COLOR MOMENTS, CO-OCCURRENCE, LOCAL COLOR HISTOG	RAM, GLOBAL COLOR HISTOGRAM AND PROPOSED APPROACH

Medical Images	Color Moments		Co-occurrence		Local Color Histogram		Global Color Histogram		Proposed Approach	
	RT	NIR	RT	NIR	RT	NIR	RT	NIR	RT	NIR
Cerebral Angiogram	71.55	450	100.71	289	143.75	550	62.47	667	322.79	285
Coronary Angiogram	47.68	886	60.86	516	78.73	890	23.65	746	193.96	506
Brain Ultrasound	26.29	670	29.24	340	32.12	498	20.00	865	93.63	335
Chest X-Ray	807.13	686	881.95	342	970.91	502	595.33	859	2799.28	334

VI. CONCLUSION AND FUTURE SCOPE

Novel approach fuzzy connectedness image segmentation with geometric moments for feature extraction from medical images is introduced in this paper. This approach is also used for retrieval of angiogram, ultrasound and x-ray medical images from large datasets. The experimentation has been carried out on the large medical image dataset of size more than 8 GB containing different types of images from angiogram, ultrasound and x-ray medical image modality in DICOM format. The proposed approach performs better compared to other approaches in terms of number precise images retrieved.

In future, we will apply the proposed approach to other medical image modalities such as computed tomography (CT), magnetic resonance imaging (MRI), and positron emission tomography (PET). The focus will be on minimizing the feature extraction and image retrieval time for the proposed fuzzy connectedness image segmentation with geometric moments.

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Amol P. Bhagat was born in Amravati, MH India, in 1984. He received the B.E. degree in information technology from Government College of Engineering Amravati, in 2005 and M.Tech. degree in computer science and engineering, Sangli, in 2009. From 2010, he is a Research Scholar with the PG Department of Computer Science, Sant Gadge Baba Amravati University, Amravati. Since 2010, he has been an Assistant

Professor with the Department of Computer Science and Engineering, Prof Ram Meghe College of Engineering & Management, Badnera. He is the author of more than 30 articles. His research interests include Image Retrieval, Image Processing and Enhancement, Soft Computing, Network Security and Distributed Computing.



Mohammad Atique, born in 1969 received the B.E. in 1990, M. E. in 1997 and Ph.D. in 2009 degrees in Computer Science and Engineering from Sant Gadge Baba Amravati University, Amravati. He is presently working as Associate Professor in PG Department of Computer Science and Engineering in Sant Gadge Baba Amravati University, Amravati. His area of interest is Image Retrieval, Image Processing, Neural Networks and Soft Computing. He is the

author of more than 70 articles and holds one patent.