Medical Image Retrieval Using Biorthogonal Spline Wavelet

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Abstract— An image retrieval system is a computer system for browsing, searching and retrieving images from a large database of digital images. So effective and fast retrieval system becomes important and the need for efficient content-based image retrieval has increased tremendously. The benefits emanating from the application of content-based approaches to medical image retrieval range from clinical decision support to medical education and research. In this paper, we propose an unsupervised approach for efficient content-based medical image retrieval that utilizes similarity measures, decomposing the images into 3 level using biorthogonal spline wavelet transform and then estimating the first two wavelet moments and placed in a feature vector. The spline wavelets based texture features, mean and standard deviation of the magnitudes of the subband coefficients in the wavelet frame decomposition are proposed for image retrieval. When given a query image, its feature vectors are similarly extracted and matched with those in the database. If the distance between the query image features and feature vector available in the database is small enough, the corresponding image in the database is considered a match to the query . The retrieval results are then ranked according to a similarity index and a group of similar target images is usually presented to the users.. It is shown that the proposed scheme can be effectively applied for medical image retrieval from large database, which can be further extended by knowledge representation methodologies.

Index terms— Biorthogonal wavelet, content-based image retrieval (CBIR), feature vector, query image.

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1 INTRODUCTION

Images have always been used in medicine for teaching, diagnosis, and management purposes. Now medical imaging systems produce more and more digitized images in all medical fields: visible, ultrasound, X-ray tomography, MRI, nuclear imaging, etc…One of the primary tools used by physician is the comparison of previous and current medical images associated with pathologic conditions. As the size of image databases had increased dramatically in recent years , new techniques and tools need to be proposed with efficient results for sorting, browsing, searching and retrieving images. Automatic image indexing using image digital content (Content-Based Image Retrieval) is one of the possible and promising solutions to effectively manage image databases .

. Content-based image retrieval - CBIR uses visual content (low-level features) of images such as color, texture, shape, etc. to represent and to index images. These features are described by multi-dimensional vectors called feature vectors that are used in the process of retrieve similar images. CBIR consists of retrieving the most visually similar images to a given query image from a database of images. CBIR from medical image databases does not aim to replace the physician by predicting the disease of a particular case but to assist him/her in diagnosis. The visual characteristics of a disease carry diagnostic information and oftentimes visually similar images correspond to the same disease category. By consulting the output of a CBIR system, the physician can gain more confidence in his/her decision or even consider other possibilities.

The benefits emanating from the application of content-based approaches to medical image retrieval range from clinical decision support to medical education and research. These benefits have motivated researchers either to apply general purpose CBIR systems to medical images or to develop dedicated ones explicitly oriented to specific medical domains. Specialized CBIR systems have been developed to support the retrievalof various kinds of medical images, including high resolution computed tomographic(HRCT) images, breast cancer biopsy slides, positron emission tomographic (PET) functional images, ultrasound images, pathology images and radiographic images.

Various techniques for CBIR have been proposed based on wavelet transform co efficient distribution unlike other time frequency transformations, the function basis is not defined by the wavelet method. So choosing the mother wavelet adapted to studied images is the obvious choice. Classical wavelets have been tested (Haar, Daubechies 9/7, Le Gall 5/3, Daubechies 4-taporthogonal...)., In 1994, Sweldens introduced a convenient way to satisfy all the desired properties of wavelets by reducing the problem to a simple relation between the wavelet and scaling coefficients. This approach is called the lifting scheme. It permits to generate any compactly supported biorthogonal wavelet. An interesting property of biorthogonal wavelet filters is that they allow a perfect reconstruction of decomposed images. All the more, the lifting scheme makes the wavelet transform faster, hence it is use in the Jpeg-2000 compression standard. Wavelet transform has several potential advantages namely,(i) Wavelet filters cover exactly the complete frequency domain. (ii) To facilitate computation fast algorithms are readily available.

In this paper we propose an unsupervised approach for efficient content-based medical image retrieval that utilizes similarity measures, decomposing the images into 3 level using biorthogonal spline wavelet transform and then estimating the first two wavelet moments and placed in a feature vector. The spline wavelets based texture features, mean and standard deviation of the magnitudes of the subband coefficients in the wavelet frame decomposition are proposed for image retrieval. When given a query image, its feature vectors are similarly extracted and matched with those in the database. If the distance between the query image features and feature vector available in the database is small enough, the corresponding image in the database is considered a match to the query.

The proposed approach combines the advantages of the clustering-based CBIR methodologies with a semantically rich representation of medical images. The major contributions of this paper are the following.

i) We define a novel representation of medical images treated as rich-in-semantics complex patterns. Each complex pattern comprises a set of simple patterns representing clusters of image regions associated with anatomic specimens in an unsupervised way. The pattern representation of cluster involvrs both structural descriptors and quality measures.
ii) We propose a novel scheme for the assessment of the similarity between complex patterns for CBIR purposes.
iii) We conduct a comprehensive set of experiments over a set of radiographic images.

This paper is organized into the following sections. Section 2 deals with the Biorthogonal spline wavelet, Section 3 describes the experimental setup with obtained results for medical images and Section 4 draws conclusions along with future perspectives

2 Biorthogonal wavelet

The biorthogonal wavelets introduced by Cohen, Daubechies, and Feauveau contain in particular compactly supported duals. In biorthogonal wavelets, separate decomposition and reconstruction filters are defined and hence the responsibilities of analysis and synthesis are assigned to two different functions (in the biorthogonal case) as opposed to a single function in the orthogonal case. In the biorthogonal case, there are two scaling functions $\phi, \tilde{\phi}$, which may generate different multiresolution analyses, and accordingly two different wavelet functions $\psi, \tilde{\psi}$. So the numbers *M* and *N* of coefficients in the scaling sequences $a, \tilde{a}$ may differ. The scaling sequences must satisfy the following biorthogonality condition

$$\sum_{n\in\mathbb{Z}} a_n \tilde{a}_{n+2m} = 2 \cdot \delta_{m,0}$$

Then the wavelet sequences can be determined as

$$b_n = (-1)^n \tilde{a}_{M-1-n}, \quad n = 0, \ldots, M-1$$ and
$$\tilde{b}_n = (-1)^n a_{M-1-n}, \quad n = 0, \ldots, N-1$$

3 Proposed Methodology

The proposed content-based medical image retrieval scheme is outlined in Fig. 1. It involves four steps: i) feature extraction from each of the registered and query image ,ii) decomposing the image using biorthogonal wavelet, iii) computing the distance between query and retrieved image. The registered of a new image into the database involves steps i)- iii), whereas step iv) is processed during the retrieval task.

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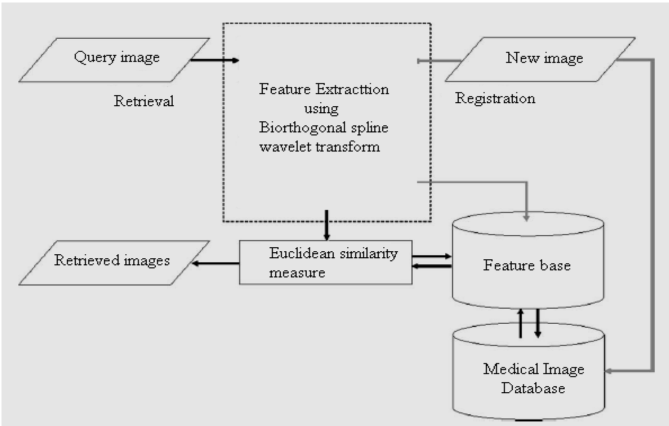

Fig. 1 . Outline of the proposed content-based image retrieval methodology

2.1 Feature Extraction

Each of the images registered in the database, as well as the query image are raster scanned with a sliding window of user defined size, sampling image blocks at a given sampling step. The sampling step may allow consecutive blocks to overlap. For each block, a set of *N* features *fi* , *i*= 1, . . ., *N*, is calculated to form a single feature vector *F*. The number of feature vectors produced for each image depends on the size, the dimensions of the sliding window, and the sampling step. Typically, the sampling parameters and the features characterizing the low-level image content are selected based on the details associated with the image collection and the retrieval task. Color, texture, and shape are the three major classes of image features commonly used in CBIR . Considering an image as a set of block samples, the features used with the proposed pattern similarity scheme should describe properly the local content of the image.

In this paper, we adopt a standard, multiscale statistical approach for the representation of the radiographic image regions that preserves local features, and does not depend on spatial coordinates. It is based on the 2-D discrete wavelet transform

2.1.1 Two dimensional discrete wavelet transform

Images are 2-D and are analyzed using a separable 2-D wavelet ttransform. A 2-D separable transform is equivalent to two 1-D transform in series. Fig.2. shows the filter bank structure for computation of a 2-D DWT.

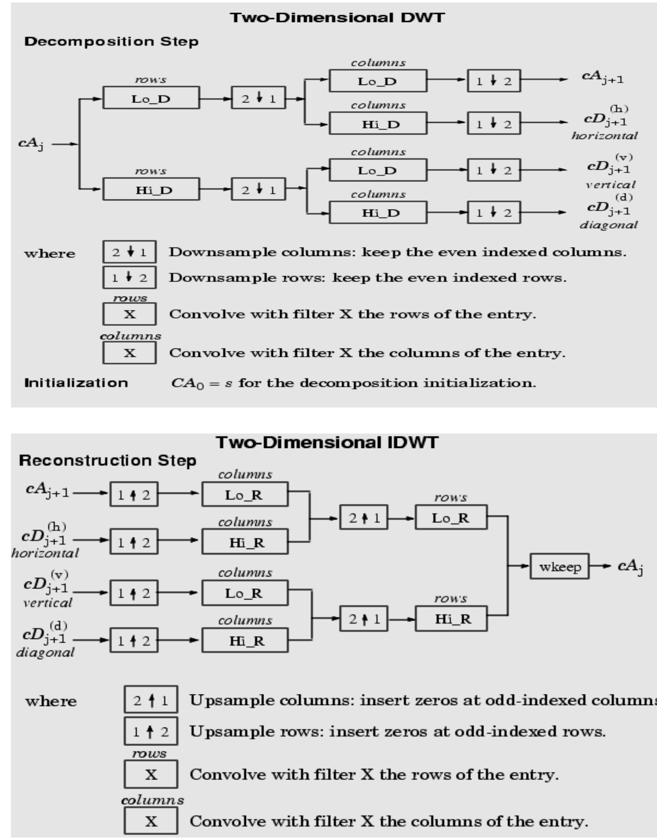

Fig.2. One level filter bank for computation of 2-D DWT.There are four basic functions for 2-D signals as given in equation (a).

$\phi(u, v) = \phi(u)\phi(v)$

$\psi_1(u, v) = \psi(u)\phi(v)$

$\psi_2(u, v) = \phi(u)\psi(v)$

$\psi_3(u, v) = \psi(u)\psi(v)$ (2.1)

$\phi(u, v)$ can be thought of as the 2-D scaling function; $\psi_1(u, v)$, $\psi_2(u, v)$ and $\psi_2(u, v)$ are the three 2-D wavelet functions. For a 2-D input signal x(u, v), the transform coefficients are obtained by projecting the input onto the four basic functions given in equation(a) . This results in four different subbands in the decomposition corresponding to the four types of transform coefficients (X(N, j, m), $X^{(1)}$(i, j, m), $X^{(2)}$(i, j, m) and $X^{(3)}$(i, j, m)). X(N, j, m) is the coarse approximation of the 2-D signal x(u; v) and corresponds to the LL band. $X^{(1)}$(i, j, m) coefficients contain the vertical details and correspond to the LH sub-band. $X^{(2)}$(i, j, m) coefficients contain the horizontal details and correspond to the HL sub-band. $X^{(3)}$(i, j, m) coefficients represent the diagonal details in the image and constitute the HH sub-band. The four subbands for one level of decomposition are shown in Figure 2.4. Thus, the 2-D DWT

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can be expressed as four inner products given by equation (2.12). As shown in Figure 2.3, it is computed by filtering each row in the image followed by filtering each column of the output obtained from the row filtering .

$X(N, j, m) = \iint x(u; v)2^N \phi(2Nu - j)\phi(2Nv - m)\, dudv$ -> LL

$X^{(1)}(i, j, m) = \iint x(u; v)2^i \psi (2iu - j)\phi(2iv - m)\, dudv$ -> LH

$X^{(2)}(i, j, m) = \iint x(u; v)2^i \phi(2iu - j) \psi(2iv - m)\, dudv$ -> HL

$X^{(3)}(i, j, m) = \iint x(u; v)2^i \psi (2iu - j)\psi (2iv - m)\, dudv$ -> HH

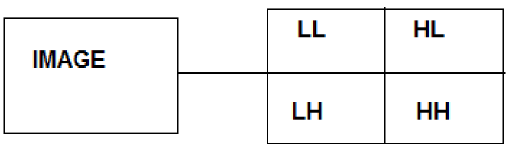

Fig. 3. Output of 1-level 2-D decomposition

Like this query and registered images undergo 3 level decomposition using biorthogonal spline wavelet transform and then estimating the first two wavelet moments and placed in a feature vector. From the available dataset, a subset of 90% of the images was registered in the database, whereas a non overlappig subset of 10% of the images is used as query image.

2.2 Eudealian similarity measure

Retrieval result is not a single image but a list of images ranked by their similarities with the query image since CBIR is not based on exact matching. For a query image indexed by FD feature fm = [$f_m^1, f_m^2, \ldots f_d^N$] and a registered image indexed by FD feature fd = [$f_d^1, f_d^2, \ldots f_d^N$], the Euclidean distance between two feature vectors can then be used as the similarity measurement:

$$D=\sqrt{\sum_{i=0}^{N-1} | f_m^i - f_d^i |^2}$$

If the distance between the query image features and feature vector available in the database is small enough, the corresponding image in the database is considered a match to the query. The retrieval results are then ranked according to a similarity index and a group of similar target images is usually presented to the users.

3 Result

A number of experiments were performed with radiographic images from the image retrieval inmedical applications (IRMA) dataset ,which is often used as a reference for medical image retrieval tasks. It currently contains 10 000 arbitrarily selected anonymous radiographic images taken randomly from patients of different ages, genders, and pathologies during medical routine. All radiographic images are in 8-bit greyscale format and have been downscaled to fit into a 256 × 256-pixel bounding box maintaining the original aspect ratio. From the available dataset, a subset of 90% of the images was registered in the database, whereas a non overlapping subset of 10% of the images was used for querying the pattern-base. Each image was sampled in blocks using overlapping sliding windows. The details of the feature extraction method used (Section 2) include a 3-level biorthogonal spline wavelet decomposition of each sampled block and the estimation of the first two wavelet moments from each band. This process results in a 20-D feature vector per block. The determination of the sampling parameters was based on preliminary experiments seeking the maximum average distance between complex patterns MI of the different categories comprising the registered dataset. The sampling parameters tested before each CBIR experiment includes sliding windows of 32 × 32, 64 × 64 and 128 × 128 pixels. In all cases, the maximum average distance was obtained with windows of 64 × 64 pixels. Variation of the overlap (0%, 25%, 50%, and 75%) between the sampled blocks did not affect this result. Increasing the overlap provides better localization of the patterns but produces many more sampled blocks, affecting the efficiency of both the feature extraction and the pattern instantiation tasks. Thus, a 50% overlap, i.e. a 32 pixel step, was used as a compromise between localization and efficiency.

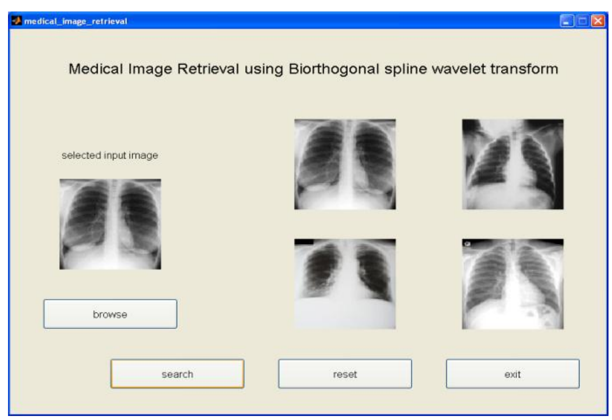

Fig.4. A query image requesting four chest images similar to the selecting image,all retrieved images belong to the same category

4 Conclusion

We presented a novel scheme for efficient content-based medical image retrieval. The results advocate both its efficiency and effectiveness in comparsion with state of the art. Future perspectives of this paper include:1) systematic evaluation of the proposed scheme for the retrieval of various kinds of medical images, such a endoscopic and ultrasound images according to their pathology;2) the enhancement of the retrieval performance by using image indexing techniques based on specialized data structures and 3) the integration of the proposed scheme with ontology-based information extraction and data mining techniques for the retrieval of medical images using heterogeneous data sources.

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