CT Image Retrieval Using Tree Structured Cosine Modulated Wavelet Transform

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***Abstract*— Developing methods for medical image characterization and indexing are in great demand for organizing and retrieving images from huge medical image databases. In this paper, novel algorithm based on tree structured cosine modulated wavelet transform (TSCMWT) for retrieval of Computer Tomography (CT) images is proposed. The proposed method performs better than existing available methods. Experimental results are promising in order to meet the requirements of the fast-paced clinical environment.**

Keywords: content based medical image retrieval, tree structured cosine modulated wavelet transform, similarity measure

I. INTRODUCTION

Medical images represent an enormous amount of data: the annual production of a single average size radiology department represents tens of terabytes of data. Therefore, petabytes of medical images are produced in developed countries each year. For these data, there is a need for long term archiving. Digital images indexing have extensively been studied for the last decade; few systems are dedicated for medical image today while the need for content-based analysis and retrieval tool increases with the growth of digital medical image databases. With the growth of medical databases, new applications devoted to statistical analysis of medical data have emerged such as lungs image analysis, cancer screening, x-ray images, skin diseases, or oncology in general. The dataset manipulated for these applications are not images of one patient or coming from one radiology department but rather images showing a particular pathology or specific features. This data set has to be dynamically assembled by automatically selected relevant images among available databases. Similarly, a physician is often interested by similar cases to the one he is studying and the similarity measurement usually involves a medical background. Retrieving of tons of medical images is only relevant if adapted query tools exist that allow medical users to browse the data sources. Hence, content-based medical image retrieval (CBMIR) has attracted much research interest in recent years. In particular, there has been growing interest in indexing biomedical images by content [1]. Manual indexing of images for content-based retrieval is cumbersome, error prone, and prohibitively expensive. Due to the lack of effective automated methods, however, biomedical images are typically annotated manually and retrieved using a text keyword-based search. A common drawback of such systems is that the annotations are imprecise with reference to image feature locations, and text is often insufficient in enabling efficient image retrieval. Even such retrieval is impossible for collections of images that have not been annotated or indexed. Additionally, the retrieval of interesting cases, especially for medical education or building atlases, is a cumbersome task. CBMIR methods developed specifically for biomedical images could offer a solution to such problems, thereby augmenting the clinical, research, and educational aspects of biomedicine. For any class of biomedical images, however, it would be necessary to develop suitable feature representation and similarity algorithms that capture the “content” in the image. Many systems were developed during the last years, both by commercial and academia. The challenge in CBIR is to develop the methods that will increase retrieval accuracy and reduce the retrieval time. Comprehensive and extensive literature survey on general purpose CBIR is presented in [2] and [3]. Despite CBIR developments, medical images are very particular and require a specific design of CBIR systems. There exists a large number of medical image acquisition devices among which computed tomography scanners (CT), magnetic resonance imagers (MRI), ultrasound probes (US) and nuclear images are the most widely used. They provide images with very different properties in terms of resolution, contrast and signal to noise ratio. They are highly specialized and they produce images giving very different information on the human body anatomy and physiology.

Some specialized CBIR have been proposed in medical applications. An image retrieval system dedicated to brain MRI which indexes images mainly on the shape of the ventricular region [5]. Korn *et al*, [6] proposed a system for fast and effective retrieval of tumor shapes in mammogram X-rays. A system which aims at helping physicians in the diagnosis of lymphoproliferative disorders of blood is described [7]. Nevertheless, a description of the clinical use of such systems is very rare, except for the systems ASSERT [9], which is dedicated to HRCT images of the lung and includes information from physicians-such as anatomical landmarks and pathology bearing regions- and IRMA which proposes a multi-step approach for the

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classification of images into anatomical areas, modalities and view points. Recently in [13] author has proposed a standard wavelet based method for CT image retrieval.

Drawback of Standard wavelet is that it is not suitable for the analysis of high- frequency signals with relatively narrow bandwidth. This has been taken care of by *M*-band wavelets, which yield improved retrieval performance. Unlike the standard wavelet decomposition, which gives a logarithmic frequency resolution, the *M*-band decomposition gives a mixture of a logarithmic and linear frequency resolution. Further as an additional advantage, *M*-band wavelet decomposition yields a large number of subbands, which helps for improving the retrieval accuracy. One of the drawback with *M*–band wavelet in CT image retrieval is that computational complexity increases with number of bands used and hence retrieval time. Since the advantages of the cosine-modulated wavelet are their low design and implementation complexities, good filter quality, and ease in imposing the regularity conditions, which yields improved retrieval performance. The texture features are more prevalent in the intermediate frequency band. This serves to motivate the present work, which increases the retrieval accuracy in image retrieval.

The main contributions of this paper are summarized as follows. In this paper novel method based on tree structured cosine modulated wavelet transforms (TSCMWT) for retrieval of Computer Tomography (CT) images is proposed. Database of 640 images is used to check the retrieval performance. The results are compared with the exiting available method. The result indicates that tree structured cosine modulated wavelet transform improves retrieval performance significantly than standard wavelet.

The paper is organized as follows. In section 2 we will discuss tree structured cosine modulated wavelet transform in brief. The proposed image retrieval procedure is given in section 3. Experimental Results are given in section 4, which is followed by the Conclusion.

II. Tree Structured Cosine Modulated Wavelet For CT Image Retrieval

Guillemot and Onno [11], proposed a cosine- modulated wavelet is used for image compression. His-Chin Hsin[12], used a modulated wavelet transform approach for texture segmentation. Here we have investigated the use of tree structured Cosine-modulated wavelet for CT image retrieval.

A. Cosine Moddulated FIR Filter Bank

An M- channel filter bank is shown in fig.1. Filter bank is said to be perfect reconstruction if $y(n)=x(n)$. A perfect reconstruction filter bank is unitary if $g_i(n)=h_i(n)$. Unitary (FIR) filter banks are practically important since they can be completely parameterized and efficiently implemented [10].

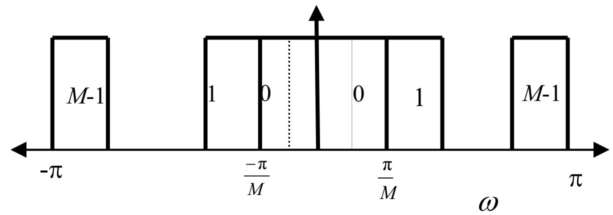

Fig.2. Ideal frequency responses in *M* channel filter

Moreover, they give rise to orthonormal wavelet bases for $L^2(\mathrm{R})$. Every unitary FIR filter bank satisfying $\sum h_0(n)=\sqrt{M}$ is associated with a wavelet tight frame and conversely. That is, if the scaling function, $\psi_0(t)$, and the $(M-1)$ wavelets, $\psi_i(t)$, are defined by

$$\psi_i(t)=\sqrt{M}\sum_k h_i(k)\psi_0(Mt-k) \quad i\in\{0,......,M-1\} \tag{1}$$

then (*M*-1) wavelets $\psi_i(t)$, $i\in\{0,......,M-1\}$, their translates and dilates by powers of *M* form a wavelet tight frame for $L^2(\mathrm{R})$. For every function $f(t)\in L^2(\mathrm{R})$ one has

$$f(t)=\sum_{i=1}^{M-1}\sum_{j,k}\langle f,\psi_{i,j,k}(t)\rangle\,\psi_{i,j,k}(t) \tag{2}$$

Where $\psi_{i,j,k}(t)=M^{j/2}\,\psi_i\left(M^j t-k\right)$.

Cosine–modulated FIR filter banks are the special class of unitary filter banks, where the analysis filters $h_i(n)$ are all cosine-modulates of a low pass linear-phase prototype filter $g(n)$.The fundamental idea behind cosine-modulated filter banks is the following: In an *M*-channel filter bank, the analysis and synthesis filters are meant to approximate ideal M^{th} band filters, which are shown in fig.2. The passband of these filters occupy adjacent frequency channels that are $\frac{\pi}{M}$ apart. Given a real, prototype filter $g(n)$ with passband in $\left[-\frac{\pi}{2M},\frac{\pi}{2M}\right]$, if it is modulated by $\cos\left((2i+1)\frac{\pi}{2M}n+\varepsilon_i\right)$, (where ε_i is arbitrary phase), has a passband equal to the desired band for the i^{th} filter in fig.2. This technique gives rise to modulated filter banks. For modulated filter bank

$$h_i(n)=h(n)\cos\left(\frac{\pi}{2M}(2i+1)n+\varepsilon_i\right) \tag{3}$$

and

$$g_i(n)=g(n)\cos\left(\frac{\pi}{2M}(2i+1)n+\gamma_i\right) \tag{4}$$

Where ε_i and γ_i are phase factors. In this work we have used filter coefficients designed by Gopinath and Burrus [14]. In the filtering stage we make use of filter coefficients for M =2 to decompose the CT image in to four channels, corresponding to different direction and resolutions. In the tree structured cosine modulated wavelet transform the energy of each subband is measured. Instead of decomposing LL subband , at next level of decomposition we decompose the subband.

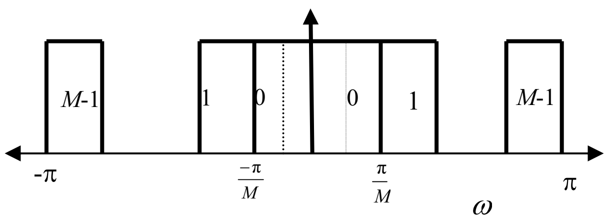

Fig.2. Ideal frequency responses in M channel filter

III. Proposed CT Image Retrieval Method

To check the retrieval efficiency of proposed method we have used texture database in our experiment, which consists of 40 different classes. The database consists of CT images of abdomen, bone, head, and lung of different cases. Those images are downloaded from open public lung image database. Size of each CT image is 512×512 . In this database there are sixteen similar images of each class, thus a database consist of 640 images.

A. *Feature Extraction*

The database of 640 CT images was analyzed using standard wavelet and tree structured cosine modulated wavelet. For constructing the feature vector, the Energy and Standard Deviation were computed separately on each subband and the feature vector was formed using these two parameter values. The retrieval performance with combination of these two feature parameters always outperformed that using these features individually. The Energy (E_k) and Standard Deviation (σ_k) of kth subband is computed as follows.

$$E_k = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \left| W_k(i, j) \right| \tag{5}$$

$$\sigma_k = \left[\frac{1}{M \times N} \sum_{i=1}^{N} \sum_{j=1}^{M} \left(W_k(i, j) - \mu_k \right)^2 \right]^{\frac{1}{2}} \tag{6}$$

where $W_k(i, j)$ is the kth wavelet-decomposed subband, $M \times N$ is the size of wavelet-decomposed subband, and μ_k is the mean value of kth subband. A feature vector is now constructed using E_k and σ_k as feature components. Resulting feature vectors from n number of total subbands are as follows:

$$\bar{f}_{\sigma\mu} = [\sigma_1 \quad \sigma_2 \quad \ldots \quad \sigma_n \quad E_1 \quad E_2 \quad \ldots \quad E_n] \tag{7}$$

Length of feature vector will be equal to $(n \times 2)$. For the creation of feature database above procedure is repeated for all the images of the image database and these feature vectors are stored the in feature database.

B. *Query Processing and Image Matching*

A query image is any one of the 640 images from image database. This image is then processed to compute the feature vector as in section III A. One can use Euclidean distance metric as similarity measure but this is not always the best metric. The fact that the distances in each dimension are squared before summation, places great emphasis on those features for which the dissimilarity is large. Hence it is necessary to normalize the individual feature components before finding the distance between the two images. This has been taken care of in Canberra distance metric as dissimilarity measure as shown in [15]. If x and y are the feature vectors of database and query image respectively of dimension d, then the Canberra distance is given by

$$\text{Canb}(x, y) = \sum_{i=1}^{d} \frac{|x_i - y_i|}{|x_i| + |y_i|} \tag{8}$$

The distances are stored in increasing order and the closest set of patterns is retrieved. The numbers of ground truth images for each query image in the database are 16. The performance is measured in terms of the average retrieval rate, which is defined as the average percentage number of patterns belonging to the same image as the query pattern in the top 16 matches.

IV. Experimental Results

Table 1: Average retrieval accuracy

	Standard Wavelet	Proposed Tree Structured Cosine Modulated wavelet
Retrieval Accuracy	**80.62 %**	**84.15 %**

Table 1 provides a comparison of average retrieval accuracy for 640 different CT images. The proposed retrieval system has been implemented using MATLAB on TABLET PC with Pentium (R) M processor, 1.2 GHz. The retrieval performance with tree structured cosine modulated wavelet has been improved up to 84.15% as compare to standard wavelet transform.

V. Conclusion

In this paper novel tree structured cosine modulated wavelet technique for CT image retrieval is presented. CT image database of 640 images is used to check the retrieval performance. Experimental results are promising in order to meet the requirements of the fast-paced clinical environment. The result indicates that tree structured cosine modulated wavelet improves retrieval performance significantly than conventional standard wavelet.

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