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Texture Based MRI Image Retrieval Using Curvelet With Statistical Similarity Matching

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Abstract

Content-based image retrieval (CBIR) is the most commonly used method for searching large-scale medical image databases. Images are generally retrieved on the basis of either low level features, such as colour,texture and shape.Most texture based image retrieval systems are still incapable of providing better retrieval result through high retrieval accuracy and less computational complexity. To tackle this problem, we propose a texture based medical image retrieval using curvelet transform with mahalanobis distance measurement. We show that the texture features are extracted by using curvelet transform and statistical similarity measure is done by using mahalanobis distance . The proposed method gives a better retrieval rate . Experimental results on a database of 200 medical images show that the proposed method significantly gives better retrieval results.

Keywords: *Content based image retrieval, discrete curvelet, similarity matching, Mahanobis distance.*

1. Introduction

Through the progress in information knowledge, there is an explosive development of image databases, which demands successful and capable tools that permit users to search through such a big collection. Usually, the majority straightforward system to execute image database managing method is by means of using the usual database-management systems such as relational databases or object-oriented databases. The method of these type is generally called meta data based image retrieval, in which the images are annotated with keywords. When the databases increases, to retrieve a exact image with these technique become tedious and it gives only poor retrieval rate. To address these problems,content-based image retrieval (CBIR) has developed.The main approaches to CBIR involved constructing image features like low level and high level**[1].** Low level image features that represent the image's contents in terms of color, shape, sketch, and texture. Mainly the image features have to be extracted from the decompressed image. However, if the features can be extracted directly from the compressed image, the speed up would be an obvious and gives better advantage particularly in applications involving extremely huge databases.The benefits originates from the application of CBIR approaches to texture based medical image retrieval vary from clinical decision support to medical research and education. These benefits have motivated researchers to apply CBIR systems to medical images . Specialized Content Based Medical Image Retrieval (CBMIR) systems have been developed to support the retrieval of different kinds of medical images, like X-ray images, computed tomography (CT),magnetic resonance imaging (MRI), positron emission tomography (PET), ultrasonography, etc. One of the main tasks in wavelet based image retrieval is to extract features without directional sensitivity.To overcome the missing directional selectivity of Discrete wavelet transform,a multiresolution geometric analysis(MGA),named curvelet transform was proposed.Similarity measurement is done by using mahalanobis distance measure which gives better results compare wih Euclidean distance.To overcome the missing directional selectivity of conventional two-dimensional (2-D) discrete wavelet transforms (DWTs), a multiresolution geometric analysis (MGA), named curvelet transform,was projected . We show that the Curvelet with mahalanobis distance measure has provided better performance than the wavelet based feature extraction .The rest of this paper is organized as follows. In section 2, we briefly explains the related work, though section 3 and 4 describe the discrete curvelet transform and curvelet based feature extraction.Section 5 and 6 explains the experimental results and the conclusion.

2. Related Work

Content Based Medical Image Retrieval (CBMIR) technology has been an active research area, and its use in medical database systems is regularly increasing**[2][3].** The purpose of medical database classification has frequently defined as the delivery of the required information at the correct time. CBMIR based image retrieval has been broad range of medical specializations Like CT images , mammograms,Magnetic Resonance Imaging(MRI) and ultrasound images**[4].**Due to the requirement of very high accuracy, the utilization of CBIR in medical diagnostics is very challenging.the use of CBMIR in medical diagnostics is the mainly significant application area.Medical Image retrieval methods need to prove their performance and it must be accepted by physicians.. In the case of medical images, the capability to retrieve similar images within a given database is very useful for diagnostic applications . Wavelet transform with euclidean distance was used for the retrieval of relevant images in the database**.** Though, this method gives less retrieval accuracy for similar images.Wavelets perform better for one dimensional signal as it is good at representing point discontinuities. All singularities in a one dimensional signal are point singularities, so wavelets have a certain universality there. However, in higher dimensions, more types of singularities may exist. In these cases wavelets lose their universality [5,6,7, 8] and perform merely good enough in capturing the edge discontinuities in 2-D space, which is important in texture representation. Another multiresolution approach, the Gabor filters, consists of a group of wavelets each of which capturing energy at a specific resolution and orientation. To overcome the problems in using the discrete wavelet and Gabor filters transform, a new multiresolution approach named discrete curvelet transform and the similarity measurement is done by using mahalanobis distance. Curvelets take the form of basis elements, which have elongated effective support; i.e. length > width [9]. Therefore, curvelets can capture anisotropic elements such as the edges of an image effectively **[5].**Furthermore, curvelet spectra cover the frequency plane of an image completely. For these important properties, curvelet transform can be used as a powerful image feature capturing tool in CBIR. Texture feature representation and its use in CBIR is an important research issue. Though many works on texture classification and representation have already been done, it is still an open issue. In order to realize the effectiveness of the curvelet features for CBIR, we make a systematic analysis**[6],** application and evaluation of this feature in this paper.

3. Discrete Curvelet Transform

Fundamentally, curvelet transform broaden the ridgelet transform to multiple scale analysis. Given an image $f(x,y)$, the continuous ridgelet coefficients are expressed in equation(1) as

$$R_f(a,b.\theta) = \iint \psi_{a,b,\theta}(x,y) f(x,y)\,dxdy \quad (1)$$

(1)

Here, a is the scale parameter where $a > 0$, $b \in R$ is the translation parameter and $\theta \in [0,2\pi)$ is the orientation parameter. Exact reconstruction is possible from these coefficients. A ridgelet can be defined in equation(2) as

$$\psi_{a,b,\theta}(x,y) = a^{\frac{1}{2}} \psi\left(\frac{x\cos\theta + y\sin\theta - b}{a}\right) \quad (2)$$

Where θ is the orientation of the ridgelet. Ridgelets are constant along the lines $x\cos\theta + y\sin\theta = const$ and transverse to these ridges are wavelets . Ridgelets take the form of a basis element and obtain a high anisotropy. Therefore, it captures the edge information more effectively. A ridgelet is linear in its edge direction and is much sharper than a conventional sinusoidal wavelet . Curvelet transform based on wrapping of Fourier samples takes a 2-D image as input in the form of a Cartesian array $f[m,n]$ such that $0 \leq m < M, 0 \leq n < N$ and generates a number of curvelet coefficients indexed by a scale j , an orientation l and two spatial location parameters (k_1, k_2) as output. To form the curvelet texture descriptor, statistical operations are applied to these coefficients. Discrete curvelet coefficients can be defined in equation (3) as

$$C^D(j,l,k_1,k_2) = \sum_{0 \leq m \leq M} f[m,n] \phi^D_{j,l,k_1,k_2}[m,n] \quad (3)$$

Here, each $\phi^D_{j,l,k_1,k_2}[m,n]$ is a digital curvelet waveform. This curvelet approach implements the effective parabolic scaling law on the subbands in the frequency domain to capture curved edges within an image more effectively. Curvelets exhibit an oscillating behavior in the direction perpendicular to their orientation in the frequency domain. Basically, wrapping based curvelet transform is a multiscale transform with a pyramid structure consisting of many orientations at each scale. At high scales, the curvelet waveform becomes so fine that it looks like a needle shaped element. Figure 1 describes the flow graph of curvelet transform. To achieve a higher level of efficiency, curvelet transform is usually implemented in the frequency domain. That is, both the curvelet and the image are transformed and are then multiplied in the Fourier frequency domain.

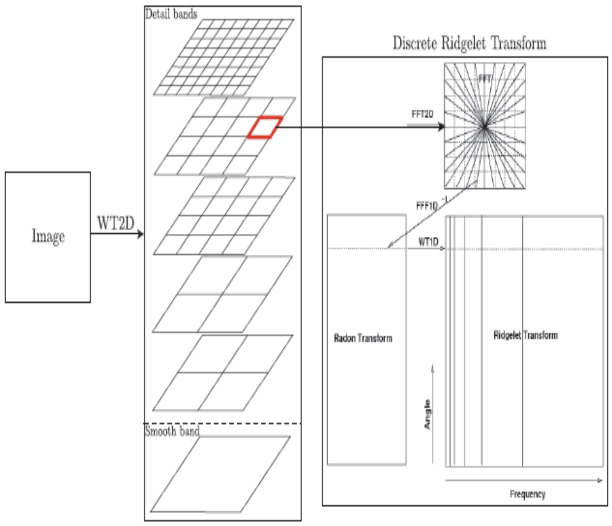

Fig. 1 Flow graph of curvelet transform

The product is then inverse Fourier transformed to obtain the curvelet coefficients. The process can be described as Curvelet transform=IFFT[FFT(Curvelet) FFT(Image)] and the product from the multiplication is a wedge.

4. Curvelet based Feature Extraction

In the earlier section, we have presented an overview of curvelet transform and enlighten why it can be expected to work better than the wavelet transform.while curvelets are good at approximating curved singularities, they are fit for extracting edge based features from medical images more efficiently than that compared to wavelet transform**[7].**

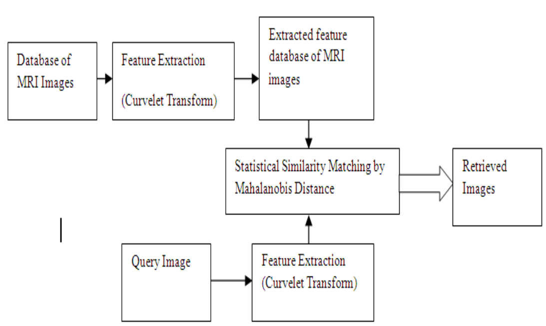

Fig. 2 Curvelet based feature extraction

We will now explain different medical image retrieval methodologies that employ curvelet transform for feature extraction.in general, a medical image retrieval method is divided into two stages: a training stage and a classification stage. In the training stage, a set of known medical images (labeled data) are used to create a representative feature-set or template. In the classification stage, a unknown medical image is synchronized against the earlier seen medical images by comparing the features. Curvelet based feature extraction take the query medical image as input. The image is then decomposed into curvelet subbands in different scales and orientations.

4.1. Statistical Similarity Matching

As a similarity measure we use the Mahalanobis standard which takes into account different magnitudes of different components.The similarity measure by a given query image involves searching the database for similar curvelet coefficients as the input query. Mahalanobis Distance is suitable and effective method over Euclidean distance measurement **[8].** The retrieved images are ranked by their similarities distance with the query image. The similarity distance measure between the vectors of query image and the database image can be shown in Figure 5. Below mentioned equation (4) shows the mahalanobis distance measurement expression, Where D is the mahalanobis distance . The computed distance is ranked according to closest similar in addition, if the distance is less than a certain threshold set, the corresponding original image is close or match the query image.

$$D^2 = (x-m)^T C^{-1} (x-m) \qquad (4)$$

Where:

x - Vector of data

m - Vector of mean values of independent variables

C^{-1}- Inverse covariance matrix of independent variables

T - Indicates vector should be transposed

Here Multirate vector $x = (x_1,x_2,x_3,\ldots,x_N)^T$ and

Mean $m = (m_1,m_2,m_3,\ldots,m_N)^T$

Mahalanobis distance for dissimilarity measure between two random vectors $\bar{x}$ and $\bar{y}$ shown in equation (5)

$$d(\vec{x},\vec{y}) = \sqrt{(\vec{x}-\vec{y})^T S^{-1}(\vec{x}-\vec{y})}. \qquad (5)$$

Precision *P* is defined as the ratio of the number of retrieved relevant images *r* to the total number of retrieved images *n*, i.e., *P* =*r*/*n*. Precision measures the accuracy of the retrieval and it is expressed in equation (6).

$$Precision = \frac{\text{No. of relevant images retrieved}}{\text{Total no. of images retrieved}} = \frac{r}{n} \qquad (6)$$

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Recall is defined by *R* and is defined as the ratio of the number of retrieved relevant images *r* to the total number *m* of relevant images in the whole database, i.e.,*R*=*r*/*m*. Recall measures the robustness of the retrieval and it is expressed in equation (7).

$$\text{Re}\,call = \frac{\text{No. of relevant images retrieved}}{\text{Total no. of relevant images in DB}} = \frac{r}{m} \quad (7)$$

5. Experimental Results

We have proposed the performance of MRI image retrieval using curvelet transform with the mahanobis distance method. First, we present the results of MRI image retrieval using the curvelet method on a data set to calculate its robustness and precision**[9].** Next, we present the comparison of curvelet with Euclidean distance,wavelet and Gabor filter formulations. Here GUI is created to evaluate the impact of the proposed technique.

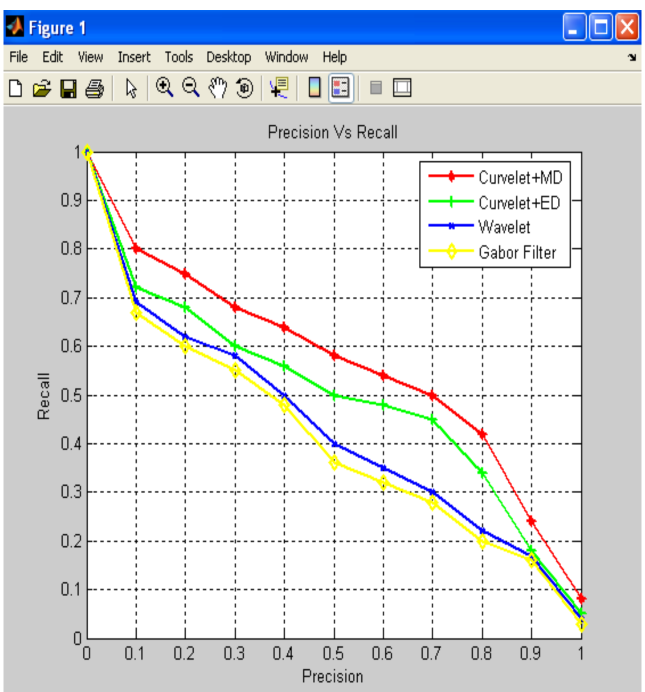

Fig. 3 Comparison of Precision Vs Recall

Similarity measures like, Recall and precision is calculated for proposed algorithm and compared with other methods depicted in figure 3.

6. Conclusions

In this paper,we have proposed a framework for MRI image retrieval using discrete curvelet transform with mahalanobis distance. The main aim of this proposed method is to increase the retrieval accuracy for texture based medical image retrieval . For this purpose, we have examined the texture analysis using wavelet with Euclidean and Gabor filter approaches. Finally, we compared the curvelet with a Mahalanobis CBIR performance with that of the existing Gabor filters and wavelet. This work has found that curvelet features outperformed the existing texture features in both accuracy and efficiency **[10].** Furthermore, curvelet texture features can also be used with PCA(Principle Component Analysis) to reduce the dimensionality for retrieved medical images. Combining discrete curvelet texture features with PCA may provide better retrieval results.

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References

[1] Lining Zhang, Lipo Wang; Weisi Lin , "Generalized Biased Discriminant Analysis for Content-Based Image Retrieval," Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on,2012, Page(s): 282 – 290

[2] Quellec, G.; Lamard, M.; Cazuguel, G.; Cochener, B.; Roux, C, "Fast Wavelet-Based Image Characterization for Highly Adaptive Image Retrieval", Image Processing, IEEE Transactions on,2012, Page(s): 1613 - 1623

[3] Zajić, Goran , Kojić, Nenad S. Reljin, Branimir D, "Searching Image Database Based On Content",IEEE Conference Publications,2011, Page(s): 1203 - 1206

[4] Akakin, Hatice Çinar ; Gürcan, Metin Nafi, "Content-Based Microscopic Image Retrieval System forMulti-Image Queries.Information Technology in Biomedicine", IEEE Transactions on,2012, Page(s): 758 - 769

[5] Ying Li; Hongli Gong; Dagan Feng; Yanning Zhang," An Adaptive Method of Speckle Reduction and Feature Enhancement for SAR Images Based on Curvelet Transform and Particle Swarm Optimization".Geoscience and Remote Sensing, IEEE Transactions on,2011,Page(s): 3105 - 3116 .

[6] Manipoonchelvi,P.; Muneeswaran, K, "Significant region based image retrieval using curvelet transform", IEEE Conference Publications,2011, Page(s): 291 – 294

[7] Liu, Sidong ; Cai, Weidong ; Wen, Lingfeng ; Eberl, Stefan ;Fulham, Michael J. ; Feng, Dagan, "Localized functional neuroimaging retrieval using 3D discrete curvelet transform", IEEE Conference Publications,2011, Page(s): 1877 – 1880.

[8] Minakshi,Banerjee, Sanghamitraand yopadhyay, Sankar K. Pal,," Rough Sets and Intelligent Systems", Volume 2,Springer link, Page(s): 391 – 395.

[9] Prasad, B. G. ; Krishna, A. N,"Statistical texture feature-based retrieval and performance evaluation of CT brain images", IEEE Conference Publications,2011, Page(s): 289 – 293.

[10] Iakovidis, Dimitris K. ; Pelekis, Nikos ;Kotsifakos, Evangelos E. ; Kopanakis, Ioannis ;Karanikas, Haralampos ; Theodoridis,Yannis, "A Pattern Similarity Scheme for Medical ImageRetriev al", Information Technology in Biomedicine, IEEE Transactions on,2009, Page(s): 442 - 450

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