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AN EFFICIENT METHOD FOR SEGMENTATION OF CT-SCAN IMAGE USING MULTIRESOLUTION ANALYSIS (MRA)

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ABSTRACT

Classification of the cancer region from the human organs by means of shape or gray-level information is a demanding task; organs shape varies throw diverse portions in medical heap and the gray-level intensity overlie in soft tissues. Multiresolution analysis based segmentation united with thresholding as pre- and post-processing steps permit accurate detection of ROIs. Curvelet transform is a newest extension of wavelet and ridgelet transforms which focuses on compacting with exciting experiences taking place along curves. This paper focuses on developing an automatic image segmentation method for classifying region of interest (ROI) in medical images which are achieved from various medical scanners such as PET, CT or MRI. The proposed segmentation system utilizes wavelet, ridgelet and curvelet transforms based Multiresolution analysis (MRA). Results attained for curvelet, wavelet and ridgelet transforms experimented on medical data sets are evaluated. Comparison results demonstrate that exploiting curvelet significantly develops the classification of abnormal tissues in the scans and diminish the adjacent noise.

Keywords: *Multiresolution Analysis, Thresholding, Wavelet Transforms, Ridgelet Transforms, Curvelet Transforms, Wrapping*

1. INTRODUCTION

For the last few decades, there is a notable increase in the use of 3D image processing particularly for medical applications. The medical image stack retrieved from the acquisition devices are complex for the analysis and visualization because of the quantity of clinical data and the amount of noise induced by the scanners itself in medical images. For this reason, computerized analysis and automated information systems can be offered for the treatment of large volume of data, and for denoising those noisy images new image processing methods may be exploited. In the vast area of image processing, MRA [1–3] and Wavelet-based features have been effectively exploited in diverse applications including image segmentation, image compression [4], denoising [5], and classification [6]. Recently, the finite ridgelet and curvelet transforms have been established as a higher dimensional MRA tool [7, 8]. Image segmentation is the process of extracting precise features from an image by means of discriminating objects from the background. The process entails the classification of each pixel of an image into a set of different classes, where the number of classes is less. Medical image segmentation involves in separating identified anatomical structures from the background such as cancer diagnosis, quantification of tissue volumes, radiotherapy treatment planning, and study of anatomical structures.

Segmentation can also be manually carried out by a human expert who merely observes an image, decides on the borders between regions, and finally classifies each region. Since the human visual system is enormously difficult and well appropriate to the task, this is possibly considered as the most trustworthy and precise method of image segmentation. However there is an inadequacy in volumetric images because of the amount of clinical data. As said, curvelet transform is a latest expansion of wavelet transform; the objective of which is dealing with the remarkable event that takes place along curved edges of the 2D images [9]. It is in general, a high-dimensional simplification of the wavelet transform proposed to characterize images at dissimilar scales and

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dissimilar orientations (angles). It is characterized as a multiscale pyramid with framework elements indicated by the parameters such as location, scale and orientation including needle-shaped elements at superior scales. Curvelets are similar to wavelets in their time-frequency localization properties. However they also exhibit a very high degree of directionality and anisotropy, and its singularities can be well estimated with only some coefficients.

The objective of this paper is designing a robust implementation of MRA methods for medical image segmentation exploiting the features derived from the medical images (obtained from a CT scanner) transformed by wavelet, ridgelet and curvelet transforms. The rest of this paper is organized as follows: Section 2 deals with a review of existing techniques for medical image segmentation. Section 3 illustrates the MRA based proposed medical image segmentation system. Section 4 presents a detail mathematical background and the methodology for the proposed MRA techniques. The experimental results and analysis of the implemented wavelet, ridgelet and curvelet transforms for medical image segmentation are demonstrated in Section 5. At last, conclusions and future work of this research is provided in section 6.

2. REVIEW OF LITERATURE SURVEY

Emmanuel Candes et. al [9] described two digital implementations of a novel mathematical transform, namely, the second generation curvelet transform in two and three dimensions. The first digital transformation is based on unequally-spaced fast Fourier transforms (USFFT) while the second is based on the wrapping of specifically chosen Fourier samples. The two implementations basically vary by the choice of spatial grid used to translate curvelets at each scale and angle. Both of their implementations were fast in the sense that they run in O (n^2 log n) flops for n by n Cartesian arrays; as well as, they are also invertible, with rapid inversion algorithms of about the same complexity. Their digital transformations developed upon prior implementations—based upon the first generation of curvelets—in the logic that they are theoretically easier, faster and extremely less redundant.

Ridgelet transform has been exploited in numerous applications including image processing; a research team used ridgelet transfomation to realize their imaging systems [10]. Linear feature detection is very significant in image processing. The detection efficiency will openly have an effect on the performance of pattern recognition and pattern classification. Based on the idea of ridgelet, they presented an original discrete localized ridgelet transform and a novel system for identifying linear feature in anisotropic images. They did various experiments to prove the efficiency of their proposed system. For a straight line in an image, the group had been employed Radon transform and Haar wavelet transform to implement ridgelet. But for a curve, the detection algorithm was very complicated. Ridgelet is merely a novel investigation tool to react some of the basic questions, such as the proficient approximation of objects with two- or higher-dimensional singularity. Ridgelet depicts common functions as a superposition of ridge functions in a steady and solid way. They advanced a latest localized ridgelet transform united with dyadic wavelet transform to discover linear feature in an image in the frame of ridgelet study.

The authors of [11] proposed a statistical distance measure between images based on the correspondence of their statistical models for classification and retrieval tasks. They described a semi Markov modeling method, in which the distributions of widths and heights of segmented regions have been formed explicitly by gamma distributions in a manner associated with clear duration modeling in HMMs. The crisis of learning their model of a given image is explained by placing the Viterbi algorithm and the probability evaluations in an iteration loop. The explanation of training system for attaining statistical image models using a hidden second order markov mesh model was their major role.

3. MRA BASED PROPOSED MEDICAL IMAGE SEGMENTATION SYSTEM

Facilitating the process of giving prominence for ROI in medical images is the major objective of this research, since the ROI may be encapsulated within other objects or enclosed by noise thus making the segmentation process tricky. Medical images are transformed using wavelet, ridgelet, and curvelet transforms along with other pre and post processing techniques to perform segmentation and ROI detection in an easier and more exact manner.

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4. METHODOLOGY—MULTIRESOLUTION ANALYSIS

Recently numerous MRA developments have been taken place, whereas wavelets are appropriate for dealing with point singularity objects. The wavelet transform extracts directional details, by means of decomposing the image into a sequence of high-pass and low-pass filter bands, which confine horizontal, vertical and diagonal directions. But, these three linear directions are limiting and are incapable of capturing adequate directional information in noisy images, such as medical CT scans, since they lack of strong horizontal, vertical and diagonal directional elements. Ridgelet transforms make use of several radial directions in the frequency domain for capturing structural information of an image. Line singularities in ridgelet transform provides enhanced edge detection than its equivalent wavelet. However the limitation in exploiting the ridgelet based image segmentation is that the linear radial structures, which are most efficiently detected by the ridgelet, are not dominant in medical images. The curvelet transform is a new extension of ridgelet transform that overcome the limitations of ridgelet in medical image segmentation. Curvelet is verified to be mainly efficient in detecting image activity along curves rather than radial directions which are the most embracing objects of medical images.

4.1. Wavelet Transform

In the previous decade, wavelet transform has been known as a dominant tool in a broad range of applications, including image/video processing, numerical analysis and telecommunication. The benefit of wavelet is that wavelet completes an MRA of a signal with localization in both time and frequency [12, 13]. Additionally, functions with discontinuities and functions with sharp spikes need fewer wavelet basis vectors in the wavelet domain when compared with sine cosine basis vectors to attain a comparable approximation. Wavelet functions by convolving the objective function with wavelet kernels to achieve wavelet coefficients signifying the offerings in the function at dissimilar scales and orientations. Along with other segmentation schemes computed exclusively within the spatial domain [14], wavelet or multiresolution theory can be employed thereby creating new systems which can present a segmentation of superior quality to those segmentation methods. Discrete wavelet transform (DWT) can be realized as a set of high-pass and low-pass filter banks. In typical wavelet decomposition, the output from the low-pass filter can be then further decomposed. In this way the decomposition process continues recursively. According to [15], DWT can be mathematically defined by:

$$x^i(n) = \sum_{m=0}^{M-1} l_p(m).x^{i-1}(2n-1), 0 \le n < N_i, \quad (1)$$

$$y^i(n) = \sum_{m=0}^{M-1} h_p(m).y^{i-1}(2n-1), 0 \le n < N_i \quad (2)$$

The coefficients $x^i(n)$ and $y^i(n)$ refer to approximation and detailed components in the signal at decomposition level *i*, correspondingly. The $l_p(m)$ and $h_p(m)$ represent the coefficients of low-pass and high-pass filters, respectively. DWT decomposes the signal into a set of resolution associated analyses. The wavelet decomposition of an image forms at each scale *i* a set of coefficient values w_i with a general mean of zero. w_i contains the similar number of voxels as the original image; hence, this wavelet transform is surplus [16, 17]. For images, 1D-DWT can be eagerly expanded into 2D. In standard 2D wavelet decomposition, the rows of image are fully decomposed, with the output being entirely decomposed column wise. In non standard wavelet decomposition, all the rows are decomposed by individual decomposition level pursued by single decomposition level of the columns.

Wavelet exploits a set of filters to decompose images based on filter coefficients and the amount of such coefficients. The most popular wavelet filter is Haar wavelet filter (HWF) which gets the averages and differences from the low- and high-pass filters correspondingly. Figure 1 demonstrates an illustration of applying 2D-DWT using HWF on an image for 2 levels of decomposition.

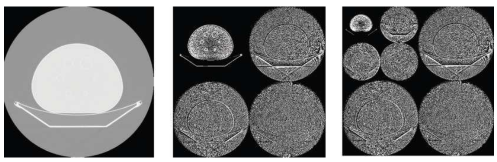

Figure 1: 2D-DWT. (a) Original Image, (b)First Decomposition Level and (c) Second Decomposition Level.

4.2. Ridgelet Transform

Ridgelet transforms [18][19] have been generating a lot of interest due to their superior performance over wavelets in compact approximations of images containing high dimensional singularities. Commonly talking,

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wavelets identify objects with point singularities, while ridgelets are able to signify objects with line singularities.

The ridgelet transform is performed in two steps: a calculation of discrete radon transform and then an application of wavelet transform. The radon transform is also performed in two steps: computation of 2D Fast Fourier Transform (FFT) for the image and then an application of a 1D Inverse Fast Fourier Transform (IFFT) on all radial directions of the radon projections. Then, 1D wavelet transform is applied limit to radial directions passing through the origin for three levels of decompositions [20].

4.2.1. Finite ridgelet transform

Once the wavelet and radon transforms have been executed, the Ridgelet transform is simple [21]. Each result of the radon projection is merely passed through wavelet transform ahead of it reaches the output multiplier. As shown in Fig. 2, ridgelets use FRAT as a basic building block where FRAT maps a line singularity into point singularity, and the wavelet transform has been employed to efficiently detect and segment the point singularity in radon domain.

Applying FRAT on an image can be described as a set of projections of the image happens at diverse angles for mapping the image space onto the projection space.

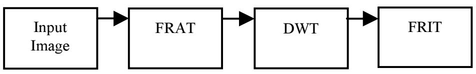

Figure 2. FRIT Block Diagram

4.3. Limitations Of Wavelet And Ridgelet Transforms

Wavelets do not separate the smoothness along edges that appears in images [22], they are hence more suitable for the reconstruction of sharp point- singularities than lines or edges. These limitations of wavelet are well overcome by the ridgelet transform; which is nothing but extending the functionality of wavelet to higher dimensional singularities, and becomes an efficient tool to carry out sparse directional study [20] [21] [23]. Segmentation results achieved by means of ridgelet transformation on medical images were not guaranteeing. Any medical image contains several curves which include most of the ROI and the other body barriers. Even after applying radon transform those curves remain as non singularity points. Thus, wavelet transform cannot identify those singularities accurately [21][24]. This explains why the ridgelet transformation is not appropriate for segmenting majority of the medical images.

Ridgelet transform can be employed in other applications where images have edges and straight lines. Curvelet transform has been established here to tackle this issue, it can identify higher singularities when evaluated with wavelet and ridgelet transforms, and could be more appropriate and reliable for medical image segmentation using MRA.

4.4. Curvelet Transform

In this new technique, the exploitation of the ridgelet transform as a preprocessing step of curvelet was rejected, thus reducing the amount of redundancy in the transform and augmenting the speed significantly [25].

$$C^D(a,b,c_1,c_2) = \sum_{0\le x\le X}^{0\le y\le Y} f[x,y]\,\vartheta^D{}_{a,b,c_1,c_2}[x,y] \qquad (3)$$

Each $\vartheta^D{}_{a,b,c_1,c_2}$ is a digital curvelet waveform, superscript *D* stands for "digital". These technique implementations are the efficient parabolic scaling law on the sub bands in the frequency domain to detain curved edges within an image in more efficient manner. As stated before, curvelet transform based on wrapping is a multiscale pyramid which includes numerous subbands at diverse scales. It consists of dissimilar orientations and positions in the frequency domain. Curvelets are so fine and looks like a needle shaped element at a high frequency level, whereas they are non-directional coarse elements at low frequency level.

To facilitate curvelet transform in achieving a higher level of efficiency it is typically implemented in the frequency domain. This implies that a 2D FFT is applied to the image. For each scale and orientation, a product of U_{ab} "wedge" is attained, the product is then wrapped around the origin, and 2D IFFT is then applied ensuing in discrete curvelet coefficients. Candes *et al* describe the discrete curvelet transform in [9] as illustrated in equation (3).

Curvelet transform= IFFT [FFT (Curvelet) X FFT (Image)] (4)

The recently constructed and enhanced version of curvelet transform is known as Fast Discrete Curvelet Transform (FDCT). This latest technique is simpler, faster and less superfluous than the original curvelet transform which is based

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on ridgelets. According to Candes et al. in [9], two implementations of FDCT are developed:

(i) Unequally spaced Fast Fourier transforms (USFFT)

(ii) Wrapping function.

Both implementations of FDCT vary chiefly by the option of spatial grid that used to translate curvelets at each scale and angle. Both digital transformations result in a table of digital curvelet coefficients indexed by a scale parameter, an orientation parameter, and a spatial location parameter. Wrapping-based transform is based on wrapping a specifically chosen Fourier samples, and it is easier to execute and realize. Fig. 3 illustrates the process of wrapping wedge where the angle θ is in the range ($\pi/4$, $3\pi/4$) and the rectangles have the same width and length as the parallelogram is centered at the origin [9].

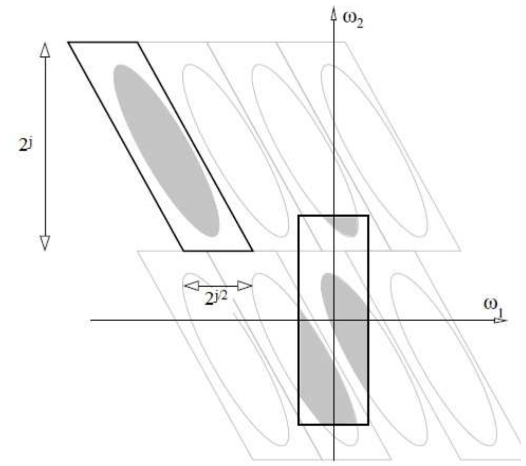

Fig. 3: Wrapping Wedge Data

The following are the steps of applying wrapping based FDCT algorithm [9]:

Step 1: Apply the 2D FFT to an image to attain Fourier samples

$$\hat{f}[x,y], -\frac{x}{2} \leq x, y < \frac{y}{2}$$

Step 2: For each scale '*a' and* angle '*b',* form the product:

$$\tilde{U}_{a,b}[x,y]\ \hat{f}[x,y]$$

Step 3: Wrap this product around the origin and obtain:

$$\tilde{f}_{a,b}[x,y] = W(\tilde{U}_{a,b}\hat{f})[x,y]$$

Where the range for x, y and θ is now $0 \leq x < 2a$, $0 \leq y < 2a/2$, and $-\pi/4 \leq \theta < \pi/4$.

Step 4: Apply IFFT to each $\tilde{f}_{a,b}$, therefore collecting the discrete coefficients $C^D(a,b,c_1,c_2)$

The curvelet transform is a multiscale transform such as wavelet, with frame elements indexed by scale and location parameters. Curvelets have directional parameters and its pyramid contains elements with a very high degree of directional specificity. The elements follow a unique scaling law where the length and the width of frame elements support are linked using equation (5):

$$\text{width} \approx \text{length}^2 \quad (5)$$

As illustrated in equation (4), the data acquisition geometry divides the curvelet expansion of the object into two parts; this is given in the following equation:

$$f = \sum_{y\in Good}\langle f,\vartheta_y\rangle\,\vartheta_y + \sum_{y\notin Good}\langle f,\vartheta_y\rangle\,\vartheta_y \quad (6)$$

The first part of the above equation can be recovered precisely while the second part cannot. What is remarkable here is that one can evidently reconstruct the recoverable part, the accuracy will be related with that one attained even if one had entire data.

Wedge wrapping is accomplished for all the wedges at every scale in the frequency domain to attain a set of subbands or wedges at each curvelet decomposition level, and these subbands are the collection of discrete curvelet coefficients. The objective is to recognize the most effective texture descriptor for medical images to capture edge information more precisely. The discrete curvelet transform can be estimated to different resolutions or scales and angles; the original image size and the angles decide the maximum number of resolution. Number of angles at the second coarsest level must be as a minimum of eight and a multiple of four; that is, 512×512 image has utmost five probable resolution levels including structural information of the image.

5. RESULTS AND ANALYSIS

Diverse datasets have been brought out with the proposed system to validate it for clinical applications. Actual clinical human images

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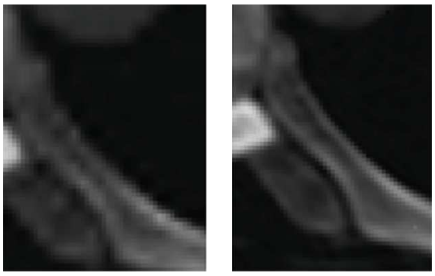
obtained by a CT scanner have also been employed to experiment the proposed model.



(a) (b)

Figure 5: Reconstruction Of Tomographic Data.Wavelet Domain (A), And Curvelet Domain (B).

Figure 5 demonstrates how curvelet-based edge reconstruction in medical imaging diverges from wavelet transform method.

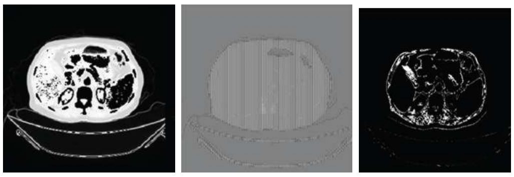


Figure 6: MRA For Real Clinical Data Segmentation.

Wavelet transforms Ridgelet transform Curvelet transform MRA techniques have been applied on the medical image to segment it and ROI is detected. Figure 6 demonstrates the outputs of applying those methods.PSNR and MSE have been also employed to estimate the quality of the proposed methods. The original image has been impured with Gaussian white noise at σ = 20% of the highest intensity.

Table 1: Comparison Of Curvelet, Ridgelet And Wavelet Denoising In Terms Of PSNR And MSE

Image Name	Curvelet denoising		Ridgelet denoising		Wavelet denoising	
	MSE	PSNR (dB)	MSE	PSNR (dB)	MSE	PSNR (dB)
NEMA	41.67	31.93	108.78	26.14	101.12	28.08

Table 1 illustrates a comparison study of curvelet transform with the other conventional transforms, and evaluation metrics PSNR and MSE have been exploited to test the quality of the transformed image. From Table 1, it is obvious that the most excellent results according to both performance metrics have been attained using curvelet transform. Moreover wavelet transform achieves improved results when compared to ridgelet transforms in both validation metrics.

6. CONCLUSION

Curvelet and ridgelet transforms are latest extension of the wavelet transform that intends to tackle with motivating events taking place along higher dimensional singularities. Though wavelets are well appropriate to point singularities, they have drawbacks with orientation selectivity thus they do not signify varying geometric features along edges efficiently. Curvelet transform shows excellent edge data reconstruction by integrating a directional component to the conventional wavelet transform. Experimental study in this report has shown that curvelet-based segmentation of the medical images not only offer good-quality reconstruction of distinguished ROI, promising results are also achieved in terms of exactly distinguishing ROI. Curvelet transform is a new tool and exploitation of this method is far from adequate in the medical image processing area. The performance metrics MSE and PSNR were evaluated for the three transformation techniques and the curvelet transformation achieved the best results for both the parameters. The future work related to this is the implementation of 3D MRA transform which can be employed directly on medical images to discover obstacle and objects or region of interest.

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