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A MEDICAL VOLUME SEGMENTATION TECHNIQUE USING 3D DISCRETE WAVELET TRANSFORM (DWT)

[1] M.NIVAS [2] Dr.M.RAMAKRISHNAN
[1]Research Scholar, Department of Computer Science and Engineering, Bharath University, Chennai
[2]Professor.,School of Information Technology, Madurai Kamaraj University, Madurai
E-mail: [1]nivasmmj@gmail.com, [2]hod.it.vec@gmail.com

ABSTRACT

3D medical image segmentation focuses at separating the voxels into 3D objects (sub-volumes) which show considerable physical entities. MRA permits for the preservation of an image based on specific levels of resolution or blurring. The superiority of this system makes it important in image compression, de-noising, and classification or segmentation. This paper aims at the implementation of a medical volume segmentation based on 3D MRA methods. Therefore, 3D discrete curvelet transform is proposed and evaluated with the discrete wavelet transform (DWT). An assessment study has been executed to evaluate 2D and 3D techniques which unveil that 3D approaches can exactly locate the region of interest in both phantom and real data.

Keywords: *A3D Image processing, Segmentation, Multi-Resolution Analysis,Discrete Wavelet Transform, Discrete Curvlet Transform.*

1. INTRODUCTION

Volume segmentation allots the voxels in 3D images into partitions or 3D regions that characterize significant physical units. The objective is to differentiate among diverse regions in the 3D volume and wrap the extracted contours from the whole volume. The categorization of Voxels into regions is done according to definite region to which the voxels fit in, and some shared, predefined possessions. Those voxels encompass a secluded or segmented Object of Interest (OOI) from the input volume. Segmentation can be physically carried out by a human expert who merely inspects an image, decides on borders between regions, and classifies each region. This is perchance the most trustworthy and precise scheme of image segmentation since the human visual system is massively complex and well adapted to the mission [1]. However when the image in issue is volumetric, performing this task does become really complex. There are numerous further existing techniques developed for medical image segmentation, including Multiresolution Analysis (MRA), statistical methods, thresholding and clustering based techniques. In clustering method each pixel in an image is classified into the suitable cluster, and then these clusters are mapped to exhibit the segmented images. For grouping each pixel into a definite number of clusters depending on the image histogram, a certain clustering standard can be implemented [1] [2].

Medical images can as well be segmented by means of thresholding techniques by partitioning their intensities. When images contain dissimilar structures with distinguishing intensities, thresholding affords an easy way for attaining segmentation. In general, the thresholds are developed based on visual evaluation of the resulting segmentation [3]. MRA permits for the conservation of an image according to definite levels of resolution or blurring. Multiresolution quality has made the wavelets being useful in image compression, de-noising, and classification. The objective of this paper is to precisely distinguish the region of interest (ROI) in the experimental data by means of different 2D and 3D schemes.

In [18], 3D DWT has been proposed for segmentation of medical volumes and they stated that the 3D Curvelet transform has not been implemented for the medical image segmentation. This could extract the curves which are occurring along many slices in medical volumes and it can offer more accurate results so far achieved in the

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medical segmentation. Therefore, this paper proposes the 3D discrete Curvelet transform for the segmentation of medical volumes and compares the performance with the 3D DWT method. A brief literature survey of similar existing schemes is presented in section 2. The mathematical background of 3D image processing is explained in section 3. In section 4, volume segmentation using 3D discrete wavelet transform (3D-DWT) is detailed. Section 5 deals with the proposed 3D Discrete curvelet transform. A comparison study has been executed to estimate 2D and 3D techniques presented in section 6 where the 3D DWT is applied on real medical data and proposed phantom data. Section 6 presents the conclusion of the work.

2. LITERATURE SURVEY

Segmentation is a major phase in the segmentation process of medical images, where user intervention is recommended as an additional source of information. This method leverages the proficient knowledge of users to produce accurate segmentation of anatomical structures, which aids measurement and diagnosis of various diseases. Numerous methods have been proposed for the segmentation however it can be further classified into the following categories [4]. They are edge based segmentation, region based segmentation, statistical approaches, graph cut based approaches and deformable modes based approaches.

Won Hwa Kim et.al have presented a method [5] to provide the multi-resolutional capabilities through non-Euclidean wavelet theory for a range of 3-D shape analysis problems in Computer Vision. They have shown that the descriptors derived from the dual domain representation provided native multi-resolution behavior to characterize the local or global topology in the region of vertices. They have proposed algorithms for perceptually meaningful shape mesh segmentation, interest point detection and surface alignment independently. Moreover, they have presented a set of comparison results on a large shape segmentation benchmark and derived a uniqueness theorem for the surface alignment problem.

Divya Kaushik et.al presented a succinct article [6] of various segmentation methodologies applied for medical image processing. It was noticeable that the utilization of the clustering methods in medical images is the recognition of damaged areas in tissues. The well-known Genetic Algorithm was applied for the segmentation of tissues in the medical MRI images.

Xinjian Chen et.al have proposed a 3-D automatic anatomy segmentation method [7] to develop their complementary strengths by combining the active appearance model (AAM), live wire (LW), and graph cuts (GC) ideas. They have constructed the AAM and trained the LW cost function and GC parameters. Moreover, a novel algorithm was proposed in the recognition phase to enhance the conventional AAM matching method. This method was combined the AAM and LW methods effectively, which has resulted in the oriented AAM (OAAM). Moreover, a multiobject strategy was utilized to help in the object initialization phase. The proposed method has consumed 5 minutes to segment one organ from the medical image.

3. MATHEMATICAL BACKGROUND

The main general way for developing 3D data set in medical applications is from tomographic devices such as computed tomography scanners (CT). Such devices are proficient in slicing an object in a physical sectioning. 3D data of those devices can be regarded as parallel slices loaded to generate a 3D volume. Each one of those slices is a 2D medical image which characterizes a particular section from the human body. By means of an algorithm given in [8], all the slices are stacked to produce a 3D matrix which estimates the 3D medical volume. The mathematical backgrounds of the proposed medical volume segmentation scheme are given in the following sub sections.

3.1. Thresholding

Scalar images can be segmented by means of thresholding techniques by partitioning image intensities. This method tries to decide an intensity value that can partition the signal into a preferred number of classes. As explained in pseudocode 1, the segmentation can be attained by clustering all pixels with intensities higher than the threshold value into one class, and the remaining pixels into another class. In numerous applications, the threshold values are selected based on the volume histogram basis and Multi-thresholding takes place when more than one threshold value is established [9][10].

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3.1.1. Pseudo code for 2D-Thresholding:

if pixel value is less than or equal to the threshold value then

set pixel value is equal to zero

end if

3D thresholding technique differs from the 2D methodology in the nature of thresholding process since 3D applies thresholding on all pixels in the volume rather than that in the plane. The pseudo code for 3D thresholding is provided in the section 3.1.1.

3.2. Pseudo Code For 3d-Thresholding

Stack 3D data set into V

[x y z]= size (V)

%apply thresholding process for each pixel in the volume

for i = 1 to x do

for j = 1 to y do

for k = 1 to z do

if Pixel value is less than or equal to the Threshold value then

set Pixel value is equal to zero

end if

end for

end for

end for

3.2. Wavelet Transform

DWT performs a convolution operation of target function with wavelet kernels to gain wavelet coefficients denoting the offerings of wavelets in the function at diverse scales and orientations. DWT can be implemented as a set of filter banks, consisting of a high-pass and low-pass filters. In standard wavelet decomposition, the output from the low pass filter can then further be decomposed; this process of decomposition is performed recursively as depicted in figure. 1, DWT can be mathematically expressed by equations (1) and (2) [11]:

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

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

The coefficients $x^i(n)$ and $y^i(n)$ refer to approximation and detailed components in the signal at decomposition level i respectively. The $l_p(m)$ and $h_p(m)$ signify the coefficients of low-pass and high-pass filters correspondingly. Wavelet transform decomposes the signal into a set of resolution associated visions. The wavelet decomposition of an image forms at each scale i, a set of coefficient values w_i, with an overall mean of zero. This set of coefficient values w_i includes the equivalent number of voxels as the novel 3D volume, and hence, this wavelet transform is superfluous [12][13]. A non-decimated or surplus wavelet transform is helpful for the discovery of excellent features within the signal.

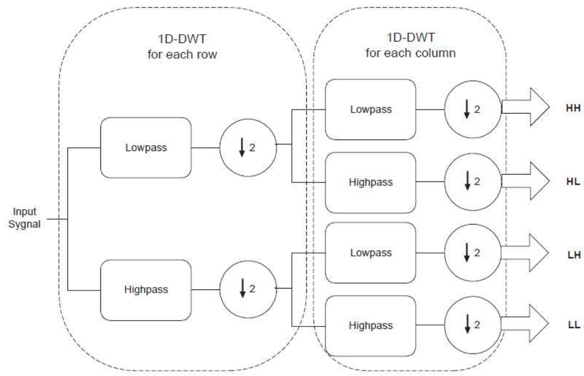

Figure 1: 2D Haar Filter Architecture

For the instant of images, the one-dimensional DWT can be willingly widened to 2D in two modes. In standard two dimensional wavelet decomposition the image is fully decomposed in row wise, while the output being entirely decomposed column wise. However in the non-standard wavelet decomposition, the entire rows are decomposed by one decomposition level followed by one decomposition level of the columns [14] [15]. The pseudocode of which is given in section 3.2.1. Fig. 2 depicts the procedure of employing 2D-DWT of Standard and non-standard wavelet transform.

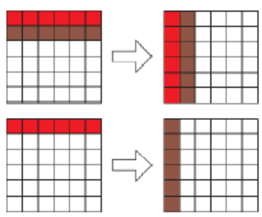

Figure 2: Sstandard and Non-Standard Wavelet Transform.

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3.2.1. Pseudocode for Standard and Non-standard decomposition:

Standard Decomposition

for each row

{do the one-dimensional decomposition}

end

for each column

{do the one-dimensional decomposition}

end

Non-Standard Decomposition

for each row %% or each column

{do the one-dimensional decomposition for one row}

{do the one-dimensional decomposition for each column}

end

4. 3D DISCRETE WAVELET TRANSFORM

It has been explained in section 3.2 that 2D-DWT is a simplification of 1D-DWT on all rows and columns using standard or non-standard decomposition. Applying 3D-DWT is not simple, the distinction between 2D images and 3D volumes is considered as the third dimension (depth or Z-axis). The 3D-DWT obtained after applying the 3D transform is depicted in figure 3, where the initial volume is transformed into 8 octants (features) in the wavelet domain which are:

LLL - LLH - LHL- LHH - HLL - HLH - HHL - HHH.

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