MEDICAL IMAGE FEATURES EXTRACTION USING THE WAVELET TRANSFORM

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ABSTRACT

Technique of dividing voxels into 3D sections (sub volumes) that correspond to significant physical things is known as 3D volume segmentation. This makes the data more understandable, easier to analyze, and useful for future applications. Multiresolution analysis, or MRA, makes it possible to preserve a picture based on specific blurring or resolution levels. Wavelets have been used for image compression, demising, and classification due to their multiresolution quality. The application of effective medical volume segmentation strategies is the main topic of this research. Feature extraction has been done using multiresolution analysis, which includes 3D wavelet and ridge let. The volume slices can be segmented using Hidden Markov Models (HMMs). The Region of Interest (ROI) can be accurately detected using 3D procedures, according to a comparison study that was conducted to assess 2D and 3D approaches.

The goal of the experimental investigation described in this work is to create an automatic image segmentation system that can classify ROI in medical pictures that are taken by several medical scanners, including PET, CT, and MRI.The suggested segmentation system makes use of multiresolution analysis (MRA) with wavelet, ridge let, and curve let transforms. Classifying malignancies in human organs using shape or gray-level information from scanner output is especially difficult since soft tissues' gray-level intensity overlaps and organ shapes vary across different slices in the medical stack. A novel expansion of wavelet and ridge let transforms, the curve let transform seeks to address intriguing phenomena that arise along curves.

I.INTRODUCTION

Medical image processing is the process of producing pictures of the human body for therapeutic purposes. It is generally understood to refer to a collection of non-invasive techniques for creating pictures of the internal anatomy of the body. This implies that cause and effect can be inferred. It is essential for enhancing the diagnosis, treatment, and prevention of sickness. A subset of biological imaging is medical imaging, which comprises radiology, nuclear medicine, investigative radiological sciences, endoscopy, thermography, medical photography, and microscopy. When an image is processed for visual interpretation, the human eye serves as the arbiter of how well a method performs.

In image processing, multiresolution analysis (MRA) has proven effective, particularly in picture segmentation. Wavelet-based features have been applied in a number of applications, such as image reduction

and classification. Each pixel in an image is categorized into a set of unique classes, with a significantly fewer number of classes. In order to diagnose cancer, measure tissue volumes, schedule radiation treatments, and research anatomical structures, medical picture segmentation attempts to isolate known anatomical structures from the backdrop.
MRA makes it possible to preserve an image at specific resolution levels. Wavelets have been proven helpful in image categorization, de-noising, and compression. Wavelet theory, which has strong mathematical underpinnings, makes use of tried-and-true techniques including pyramidal image processing, sub band coding, and quadrature mirror filtering.
Wavelet analysis makes it possible to take advantage of signal or image properties linked to a specific resolution level that other analysis methods might miss.
A hidden sequence of states that the model went through to produce the emissions is observed by statistical models that use Hidden Markov Models (HMMs) to analyze a series of emissions. Although the observer cannot directly see HMM states, they can see the variables that are affected by them. Every state in HMM evaluates the state sequence using a probability distribution across the other states. Finding the hidden parameters from the observable parameters to be used in additional analysis is the difficult part of HMM.
Computer-aided diagnostics (CAD) is a technique that allows a physician to quickly and easily establish a diagnosis by extracting useful information from medical photos. However, due of the human body's irregular structure, it might be challenging to identify problems in medical photos, such as noise levels or improper format. In order to process, analyze, and create images, image processing technology is essential. Identifying edges in an image will help us understand the image feature.

The goal of all traditional computer vision is to electronically perceive and analyze images in order to mimic the effects of human vision. Making computers able to see is a challenging task.

Whether a computer vision system's functionality is pre-defined or if certain aspects of it can be learned or altered while in use also affects how it is implemented. Nonetheless, the majority of computer vision systems have a number of standard features.

Dennis Gabor was the first to suggest Gabor functions as a means of detecting signals in noisy environments. In space, Gabor demonstrates that attempting fine sampling leads to coarse frequency sampling and vice versa."The Heisenberg principle"
• In the conjoint space-frequency domain, the minimal region for sampling is limited by the product of space and frequency.
•Gabor noted that the Gabor function provides the lowest resolution in the joint frequency-space domain.
In this instance, a complicated sine wave with variable frequency modulation using a fixed Gaussian is used to generate gabor functions.

II.**CAD SYSTEM STEPS**

2.1. IMAGEACQUISITION

A range sensor, a tomography machine, radar, an ultrasonic camera, or another type of light-sensitive camera can all provide a digital image. A 2D image, 3D volume, or image sequence are the picture data that is generated, depending on the type of sensor. In addition to being associated with physical factors such as depth, nuclear magnetic resonance, acoustic or electromagnetic wave absorption or reflectance, or light intensity in one or more spectral bands (grey or color images), pixel values can also affect these physical characteristics.

2.2. PRE-PROCESSING

Prior to extracting a particular piece of information using a computer vision approach, the data must be analyzed to make sure it satisfies the assumptions of the method. For instance, noise reduction is used to make sure that

1. Sensor noise doesn't introduce inaccurate information.
2. Re-sampling to guarantee the accuracy of the image coordinate system.
3. Contrast enhancement to guarantee the visibility of crucial information.
4. Enhancement of image structure through scale-space representation at scales that is pertinent to the local context.

2.3. FEATURE EXTRACTION

The input data of an algorithm is converted into a reduced representation of a collection of features (also known as a features vector) when it is too large to examine and is suspected of being notoriously redundant (data with little information). Making a collection of features out of raw data is known as features extraction. If the features are carefully chosen, the features set should be able to extract useful and significant information from the input data so that the necessary task can be carried out using this reduced representation rather than the full size input (for instance, in medical imaging, extract anatomical boundaries before comparing with a normal template and diagnosing). These features are frequently lines, edges, and ridges. Localized points of interest include blobs, points, and corners. More complicated attributes may be linked to texture, form, and motion. To identify and categorize abnormalities in medical images, feature extraction approaches include wavelets, statistical methods, and the majority of them use features generated using image processing techniques. Fuzzy theory and neural networks are further methods.

2.4. SEGMENTATION

Segmentation, as the name suggests, is the process of breaking up a digital image into several pieces, or groups of pixels called super pixels. Segmentation aims to simplify and/or alter an image's representation in order to make it easier to comprehend and assess. A method for locating objects and boundaries (such as lines, curves, etc.) in photos is called image segmentation. To put it another way, image segmentation is the process of assigning a label to every pixel in a picture so that those pixels share specific visual characteristics. A collection of segments or contours that encompass the entire image is produced by the image segmentation method. A region's pixels are all comparable in terms of color, intensity, or texture.

2.5. GROUPING

In this stage, we have a small set of data, typically a region of an image or a collection of points that is believed to contain a certain item. For instance, the residual processing addresses:
1. Determining features unique to an application, like item sizes and positions.
2. verifying that the data satisfies assumptions based on the model and the application.
3. Assigning various categories to the found object.

III.**MULTIRESOLUTION ANALYSIS**

In recent years, image segmentation employing MRA, such as wavelets, has been popular since it offers improved accuracy in separating various image kinds. Wavelets can be used to cope with objects that exhibit point singularities, and MRA has seen several recent advancements. Wavelets' weak orientation selectivity limits their ability to record directional information. In

order to recover directional information that capture horizontal, vertical, and diagonal activity, the wavelet transform breaks down the image into a sequence of high-pass and low-pass filter bands. Due to their limitations, these three linear directions

may not be able to adequately capture directional information in noisy pictures, like medical CT scans, which lack prominent horizontal, vertical, or diagonal directional features.

Ridgelet enhances MRA segmentation, but they also record an image's structural information based on several radial directions in the frequency domain. Compared to its wavelet predecessor, the ridgelet transform's line singularities offer superior edge identification.
The fact that ridgelet is best at identifying linear radial structures—which are not prevalent in medical images—is one drawback to using it for image segmentation. A more recent development that addresses ridge let's shortcomings in medical image segmentation is the curvelet transform. It has been demonstrated that Curvelet is very good at identifying picture activity along curves rather than radial directions, which are the most common items in medical images.

IV. **WAVELET TRANSFORMATION**

Wavelet transform has gained recognition as a potent tool in the past ten years for a variety of uses, such as telecommunication, image and video processing, and numerical analysis. Wavelets provide the advantage of performing a signal's MRA with localization in both time and frequency. Furthermore, compared to sine and cosine basis vectors, functions with discontinuities and abrupt spikes require less wavelet basis vectors in the wavelet domain to provide a comparable approximation. In order to obtain wavelet coefficients that represent the contributions in the function at various scales and orientations, wavelet operates by convolving the target function with wavelet kernels. When combined with segmentation techniques, wavelet theory can be utilized to create novel systems that can produce segmentation of higher quality than those segmentation techniques that are solely calculated inside the spatial framework.
Discrete wavelet transform (DWT) can be implemented as a set of high-pass and low-pass filter banks. In standard wavelet decomposition, the output from the low-pass filter can be subsequently decomposed further, with the process continuing recursively in this manner.
1D-DWT is easily extended into 2D for photos. The result of typical 2D wavelet decomposition is fully decomposed column wise, with the picture rows entirely decomposed. In nonstandard wavelet decomposition, one decomposition level breaks down each row, and then one decomposition level breaks down each column. The 2D-DWT filters structure.
Images are broken down by Wavelet using a set of filters based on the number of filter coefficients.
The Haar wavelet filter (HWF), which uses the averages and differences from the low- and high-pass filters, respectively, is the most often used wavelet filter. An example of applying 2D-DWT with HWF to an image for two layers of decompositions.

4.1. *DISCRETE WAVELET TRANSFORM*

A collection of filter banks, including high-pass and low-pass filters, can be used to construct the discrete wavelet transform (DWT). The output from the low-pass filter can then undergo additional decomposition using typical wavelet decomposition, with the process repeating recursively.
The signal is broken down into a collection of resolution-related perspectives by DWT. An image's wavelet decomposition yields a set of coefficient values wj at each scale j, with a zero overall mean. This wavelet transform is unnecessary because the number of voxels in this set of coefficient values wj is equal to that of the original 3D volume.
For the purpose of detecting fine characteristics in the signal, a non-decimated or redundant wavelet transform is helpful. It is easy to expand the one-dimensional DWT to two dimensions for the situation of photographs. The output is entirely decomposed column wise once the image rows are fully decomposed in typical two-dimensional wavelet decomposition. One decomposition level breaks down each row in nonstandard wavelet decomposition, and then one decomposition level breaks down each column.

4.2. *DISCRETE WAVELET PACKET TRANSFORM*

In contrast to the DWT-based method, the Wavelet Packet (WP) wavelet transform passes the data through additional filters.
Four coefficients are produced when DWT or WP is applied to images; three of them are detail coefficients, while the fourth is the average coefficient. It is important to note that both DWT and WP go through the same initial degree of decomposition.

Detail coefficients, which are obtained by applying the subsequent DWT decomposition to the average coefficients from the preceding decomposition, show the distinctions between DWT and WP. Every prior decomposition coefficient is subjected to the subsequent WP decomposition.
When DWT and WP are applied to a phantom slice at different levels of decomposition, the details quadrants in WP are altered, but the average quadrants in both DWT and WP are the same. As the decomposition level is raised by 1, the number of DWT quadrants increases linearly by 3

4.3. 3*D DISCRETE WAVELET TRANSFORM*

It has been shown that, when applied to all rows and columns using either standard or non-standard decomposition, 2D-DWT is a generalization of 1D-DWT.It is difficult to apply 3D-DWT; the third dimension, often known as the Z-axis or depth, is what separates 2D images from 3D volumes.
In the wavelet domain, the original volume is converted into eight octants, or features. After applying 2D-DWT to all of the composing frames, 3D-DWT is mathematically defined as the process of applying 1D-DWT to any vector in Zaxis that has the same X-axis and Y-axis coordinates. Algorithm 4 describes the filter structure of the 3D Haar wavelet transform as well as the pseudo code for applying 3D-DWT on 3D datasets.
One of the most often used denoising methods is wavelets, which can distinguish between information and noise in a signal. In essence, a signal or image's wavelet coefficients are calculated using an agiven wavelet transform and then thresholded. After replacing wavelet coefficients below a threshold with zeros (a process known as "hard thresholding"), the inverse discrete wavelet transform is used to rebuild the signal or image.
One crucial component of image processing is reducing the amount of noise in pictures. The process of de-noising involves restoring a signal that has been distorted by noise. The resulting coefficients from discrete wavelet decomposition can be changed to remove unwanted signal components. In order to use wavelet thresholding, a wavelet shrinkage technique for picture de-noising has been validated.

V. **1DIMENSIONAL TO 2-DIMENSIONAL**

A planer sinusoid multiplied by a two-dimensional Gaussian makes up the 2-dimensional Gabor wavelet. The sine wave is triggered by the image's frequency information, and the Gaussian makes sure that the region of the image near the wavelet's center dominates the convolution.

•The wavelet's properties regulate its size, aspect ratio, frequency, phase, and orientation.
•The picture's frequency information activates the sine wave, and the Gaussian ensures that the region of the image near the wavelet's center dominates the convolution.
It is important to convolve the location with numerous wavelet instantiations in order to adequately characterize the frequency information of a feature in an image. This instance conducts sampling in various orientations and at various frequencies.

VI. **WAVELET PICTURE NOISE REDUCTION**

Wavelet selection (e.g., Haar, symmlet, etc.) and the number of scales or levels for the decomposition.
Calculating the noisy image's forward wavelet transform The process involves estimating a threshold, selecting a shrinkage rule, and applying the threshold to the detail coefficients. Either hard or soft thresholding can be

used to achieve this. Using the changed (threshold) coefficients to apply the inverse transform (wavelet reconstruction). One method for signal and image denoising is thresholding. How we apply the threshold is defined by the shrinkage rule.

The process's outcomes are shown for a simulated noisy volume processing. Using a particular algorithm based on wavelet coefficient values, threshold limits are computed independently for each subvolume coefficient. the entire procedure for a chosen volume slice, which begins with the simulated volume and ends with its reconstruction following the first level's breakdown.

The vessel volume has been subjected to the wavelet decomposition scheme for a single scale of decomposition (1 approximation, 7 details). The size of each octant is divided by two in relation to the processed volume's initial size. The simplest orthogonal wavelet basis, the Haar basis, was used to create these octants following a one-level 3D wavelet transform. Compared to the low-pass one LxLyLz, we can see that the detail octants display more textures and curves. Compared to high-

pass octants, the low-pass octant has more energy (visual vessel filament structures). The new approximation subband is further decomposed after one scale of decomposition along each direction, yielding a same number of samples in the subbands as in the original finest resolution image.

Volumetric data registration and biomedical image processing constitute a broad research field with numerous applications. An illustration of vertebral volume data utilized for diagnosis and the identification of health issues. Volumetric segments must be classified based on their characteristics.

VII.IDENTIFICATION OF VOLUME COMPONENTS

To facilitate accurate diagnosis and therapy, volume components of the vertebral data are extracted from the primary processing objective. The foundation of the investigation is basic data segmentation features. The initial research demonstrated that wavelet decomposition may be used once more to identify texture complexity and its energy distribution.
For every volumetric segment discovered, the algorithm specifies a method of this kind.
Algorithm B: Feature extraction, wavelet transform application for a chosen wavelet and decomposition level, energy calculation inside the image detail sub band, and energy component selection to create the feature vector.
Neural networks and other chosen clustering techniques can then be used to classify feature vectors into the specified number of classes

VIII. RESULTS

Radiologists and other experts who analyze medical images to diagnose cancer are the system's end users. Following a number of talks with those working in radiology departments at various hospitals, their primary objective is to identify the precise cancer size in medical photos with the least amount of inaccuracy. The noise around ROI may have an impact on this process.
The difficult procedure of precisely assessing the lesion's dimensions. The suggested system has been tested on several datasets to ensure that it is suitable for clinical use. The first is the NEMA IEC body phantom, which has six spherical inserts
hung by plastic rods with inner diameters of 10, 13, 17, 22, 28, and 37 mm inside an elliptical water-filled chamber. Additionally, experiments have been conducted using actual clinical human images obtained by a CT scanner.

The radiologists have already examined this data, and the papers they have provided clarify that the patients have been diagnosed with cancer. Shows the SNR values of features that were retrieved from the NEMA IEC DATA SET in the spatial domain, at various wavelet block sizes, and at various wavelet decomposition levels. The noise from the acquisition systems itself is the reason why all strategies have yielded low SNR values. Following the reconstruction of every slice, this noise will be a component of the medical image. Better SNR values can be obtained with the second level of wavelet decomposition, and the modified image becomes more like the original as the block size (p) increases with the wavelet transform.

The main drawback of applying Wavelet transformation to medical picture segmentation is that ridges are rarely seen in such data.

Experimental data has been segmented using MRA transforms and thresholding. As a preprocessing phase, the threshold approach has been used on the original photos at a threshold value (t = 35) to exclude as much fraudulently generated content as possible from the scanners. After applying the transform to accurately depict objects with edges, which are the contours of the medical images, a second thresholding is applied at (t = 7) to eliminate the majority of the residual noise and make the measurement process easier.

Because the examined data set lacks ridges or straight lines, the wavelet transform detects ROI but does not produce encouraging segmentation results. The quality of the wavelet quadrants varies as well; in comparison, the LL-filter output has produced the best results. The diameters of the spheres have been measured using ED, and the error percentages for each method and sphere diameter error.

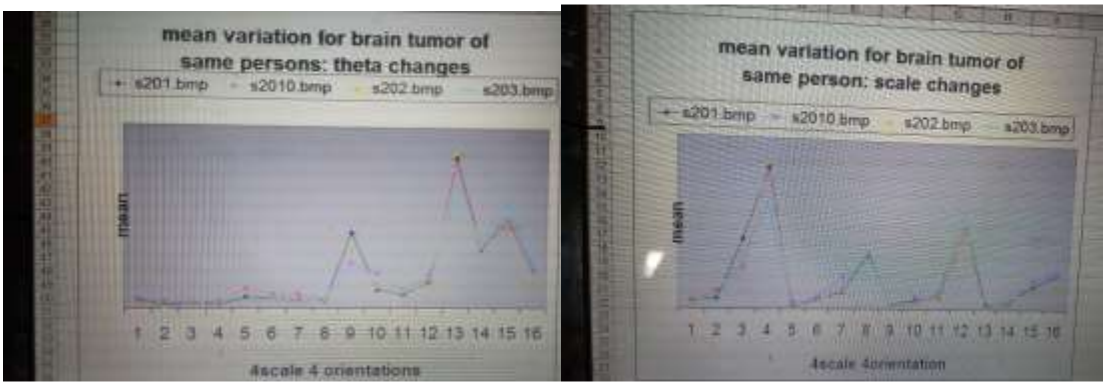

Fig.8.1.Experimental Results

VIII.CONCLUSION

The study contributes to the analysis of the vertebral volume using the three-dimensional wavelet transform. Initially, volumetric data de-nosing was accomplished using the general technique of multi-resolution volume decomposition and reconstruction in conjunction with wavelet coefficient thresholding. The segmentation and classification of volume elements is discussed in more detail in relation to the usage of wavelet transforms for feature extraction. The suggested techniques were then employed for actual volumetric data processing to extract their components required for a correct analysis, diagnosis, and medical treatment. The resulting algorithms were used to compare various wavelet functions for rejection of additional noise.
The application of statistical models, complicated wavelet transforms, 3D registration, segmentation, and visualization in relation to the detailed physiological interpretation of results will all be the focus of more mathematical analysis.
The segmentation approach employing multiresolution analysis in conjunction with thresholding as a pre- and post processing phase enables precise ROI detection because of the shifting forms of organs in medical pictures. Medical picture segmentation makes considerable use of multiresolution analysis, such as wavelet transform, which yields more accurate results.

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