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MULTIRESOLUTION ANALYSIS USING WAVELET TRANSFORMS FOR MEDICAL IMAGE SEGMENTATION

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ABSTRACT: The experimental study presented in this paper is aimed at the development of an automatic image segmentation system for classifying region of interest (ROI) in medical images which are obtained from medical scanners like MRI. Multiresolution analysis (MRA) using wavelet transforms has been used in the proposed segmentation system. It is particularly a challenging task to classify cancers in human organs in scanners output using shape or gray-level information; organs shape changes throw different slices in medical stack and the gray-level intensity overlap in soft tissues. This paper presents the application of wavelet transform to perform these task using the three dimensional waveletdecomposition, coefficients thresholding and object reconstruction. The proposed method is verified for simulated data at first and then applied for processing of brain parts to emphasize its selected components. The goal of the paper is in (i) the presentation of the three-dimensional wavelet transform, (ii) discussion of its use for volume data denoising, and (iii) proposal of the following data extraction to allow their classification. The paper compares numerical results achieved by the use of different wavelet functions and thresholding methods with the experience of an expert to propose the best algorithmic approach to this problem.

KEYWORDS: Multiresolution analysis (MRA),DWT, decomposition, Reconstruction, thresholding.

INTRODUCTION:

In the last decade, the use of 3D image processing has been increased especially for medical applications; this leads to increase the qualified radiologists' number who navigate, view, analyze, segment, and interpret medical images. The analysis and visualization of the image stack received from the acquisition devices are difficult to evaluate due to the quantity of clinical data and the amount of noise existing in medical images due to the scanners itself. Computerized analysis and automated information systems can offer help dealing with the large amounts of data, and new image processing techniques may help to denoise those images.

Multiresolution analysis (MRA) [1–3] has been successfully used in image processing specially with image segmentation, wavelet based features has been used in various applications including image compression [4], denoising [5], and classification [6]. The process involves classifying each pixel of an image into a set of distinct classes, where the number of classes is much smaller. Medical image segmentation aims to separate known anatomical structures from the background such cancer diagnosis, quantification of tissue volumes, radiotherapy treatment planning, and study of anatomical structures.

Segmentation can be manually performed by a human expert who simply examines an image, determines borders between regions, and classifies each region. This is perhaps the most reliable and accurate method of image segmentation, because the human visual system is immensely complex and well suited to the task. But the limitation starts in volumetric images due to the quantity of clinical data.

Multi-dimensional data analysis [7, 8] and multi-resolution modeling form a specific area of digital signal processing with many interdisciplinary applications having the common mathematical background. The interest in this area is closely connected with the three-dimensional modeling and visualization.

The main goal of the paper is to show the denoising algorithms based upon the discrete wavelet transform (DWT) that can be applied successfully to enhance noisy multidimensional magnetic resonance (MR) data sets including the two-dimensional (2-D) image slices and three-dimensional (3-D) image volumes. Noise removal or denoising is an important task in image processing used to recover a volume data that has been corrupted by noise. The application of the proposed algorithms is mainly in the area of magnetic resonance imaging (MRI) as an imaging technique used primarily in medical field [14, 12] to produce high quality images of the soft tissues of the human body. An insight to the visualization of MRI data sets i.e. 2-D image slices or 3-D image volumes is of paramount importance to the medical doctors. The discrete wavelet transform [6,9,10,11] plays an increasingly important role in the denoising of MR images. The three-dimensional (3-D) digital image processing, and in particular 3-D DWT, is a rapidly developing research area with applications in many scientific fields such as biomedicine, seismology, remote sensing, material science, etc [19].

The 3-D DWT algorithms are implemented as an extension of the existing 2-D algorithms. The performance of the denoising algorithms is quantitatively assessed using different criteria namely the mean square

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error (MSE), peak signal-to-noise ratio (PSNR) and the visual appearance. The results are discussed in accordance to the type of noise and wavelets implemented. This paper is focusing on a robust implementation of MRA techniques for segmenting medical volumes using features derived from the wavelet transform of medical images obtained from a MRI scanner.

PROPOSED MEDICAL IMAGE SEGMENTATION:

The main aim of this research is to facilitate the process of highlighting ROI in medical images, which may be encapsulated within other objects or surrounded by noise that make the segmentation process not easy. Figure 1 illustrates the proposed medical image segmentation system using MRA. Wavelet transform are applied on medical images with other preprocessing and post-processing techniques to present segmented outputs and detected ROI in an easier and more accurate way.

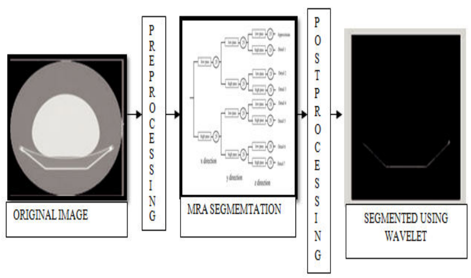

Fig 1: Proposed segmentation system for medical images.

THREE DIMENSIONAL WAVELET DECOMPOSITION:

Wavelet transform [6, 12, 11,9] provides mathematical tools for time-scale signal analysis in the similar way as the short time Fourier transform (STFT) in the time-frequency domain. The main difference is in the use of time limited analysing wavelet functions allowing different scale resolution for dilated initial wavelet. Wavelet series constructed with two parameters, scale and translation, provide in this way the ability to zoom in on the transient behavior of the signal. The continuous wavelet transform [16] is defined as the convolution of $x(t)$ with a wavelet function, $W(t)$, shifted in time by a translation parameter b and a dilation parameter a (Eq. (1))

$$X_W(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} W\left(\frac{t-b}{a}\right) x(t)dt \qquad (1)$$

The discrete form of the wavelet transform is based upon the discretization of parameters (a, b) on the time-scale plane corresponding to a discrete set of continuous basis functions. This can be achieved defining

$$W_{j,k}(t) = \frac{1}{\sqrt{a_j}} W\left(\frac{t-b_k}{a_j}\right) \qquad (2)$$

Two popular choices for the discrete wavelet parameters a0 and b0 are 2 and 1 respectively, a configuration that is known as the dyadic grid arrangement resulting in

$$\begin{aligned} W_{j,k}(t) &= a_0^{-j/2}\ W(a_0^{-j}\ t - kb_0) \\ &= 2^{-j/2}\ W(2^{-j}\ t - k) \end{aligned}$$

Wavelet analysis is simply the process of decomposing a signal into shifted and scaled versions of a mother (initial) wavelet. An important property of wavelet analysis is perfect reconstruction, which is the process of reassembling a decomposed signal or image into its original form without loss of information. For decomposition and reconstruction the scaling function Φjk(t) and the wavelet W jk(t) are used in the form

$$\Phi_{jk}(t) = 2^{-\frac{j}{2}}\ \Phi_0(2^{-j}\ t - k) \qquad (3)$$
$$W_{jk}(t) = 2^{-\frac{j}{2}}\ \Psi_0(2^{-j}\ t - k) \qquad (4)$$

Where m stands for dilation or compression and k is the translation index. Every basis function W is orthogonal to every basis function Φ. The one-dimensional wavelet transform of a discrete time signal x(n) (n =0 ,1,...,N) is performed by convolving signal x(n) with both a half-band low-pass filter L and high-pass filter H and down sampling by two.

$$c(n) = \sum_{n=0}^{L-1} h_0(k)\, x(n-k) \qquad d(n) = \sum_{n=0}^{L-1} h_1(k)\, x(n-k) \qquad (5)$$

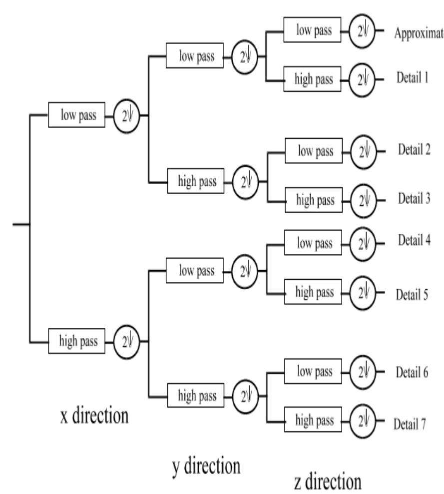

Fig 2: 3D DWT filter structure.

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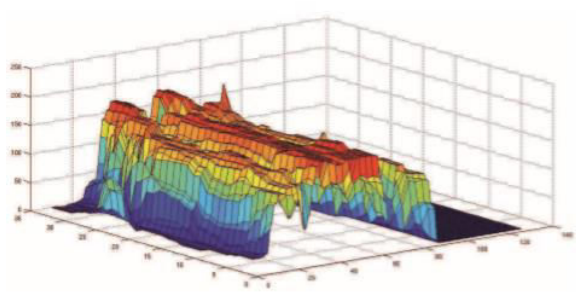
Wavelet Transform. In the last decade, wavelet transform has been recognized as a powerful tool in a wide range of applications, including image/video processing, numerical analysis, and telecommunication. The advantage of wavelet is that wavelet performs an MRA of a signal with localization in both time and frequency [10, 11]. In addition to this, functions with discontinuities and functions with sharp spikes require fewer wavelet basis vectors in the wavelet domain than sine cosine basis vectors to achieve a comparable approximation. Wavelet operates by convolving the target function with wavelet kernels to obtain wavelet coefficients representing the contributions in the function at different scales and orientations. Wavelet or Multiresolution theory can be used alongside segmentation approaches, creating new systems which can provide a segmentation of superior quality to those segmentation approaches computed exclusively within the spatial domain [12]. 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 then decomposed further, with the process continuing recursively in this manner.



The ability of wavelets to separate noise from information contained in a signal makes them one of the most popular denoising techniques. Basically speaking, wavelet coefficients of a signal or image are computed using a given wavelet transform and are then thresholded. Wavelet coefficients below a threshold can be replaced by zeros (hard thresholding procedure), and the signal or image is then reconstructed using the inverse discrete wavelet transform.

The reduction of noise present in images is an important aspect of image processing. De-noising is a procedure to recover a signal that has been corrupted by noise. After discrete wavelet decomposition the resulting coefficients can be modified to eliminate undesirable signal components. To implement wavelet thresholding a wavelet shrinkage method for de-noising the image has been verified. The proposed algorithm to be used consists of the following steps:

Algorithm A: Wavelet image de-noising

• Choice of a wavelet (e.g. Haar, symmlet, etc) and number of levels or scales for the decomposition. Computation of the forward wavelet transform of the noisy image • Estimation of a threshold

• Choice of a shrinkage rule and application of the threshold to the detail coefficients. This can be accomplished by hard or soft thresholding

• Application of the inverse transform (wavelet reconstruction) using the modified (thresholded) coefficients.

Thresholding is a technique used for signal and image denoising. The shrinkage rule define how we apply the threshold. There are two main approaches which are:

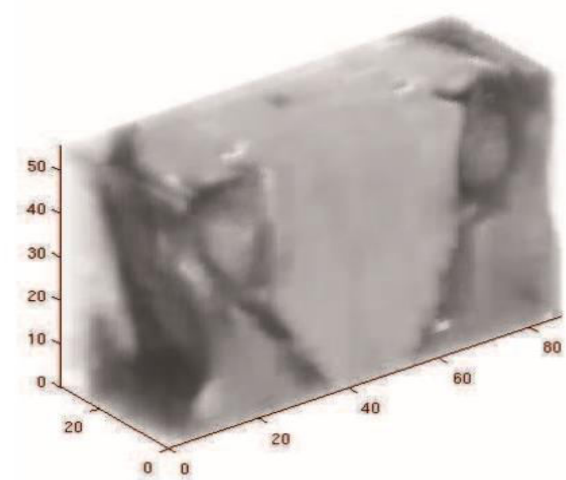


Fig: 3 3D denoising using Haar Wavelet transform

We can clearly see that the Haar basis (haar) is not appropriate for image denoising since the computed PSNR is smallest compared to all wavelet bases.

• Hard thresholding deletes all coefficients that are smaller than the threshold λ and keeps the others unchanged. The hard thresholding is defined by relation

$$\bar{c}_s(k) = \begin{cases} \text{sign } c(k)\ (|c(k)|) & \text{if } |c(k)| > \lambda \\ 0 & \text{if } |c(k)| \leq \lambda \end{cases}$$

Where λ is the threshold and the coefficients that are above the threshold are the only ones to be considered. The coefficients whose absolute values are lower than the threshold are set to zero.

• Soft thresholding deletes the coefficients under the threshold, but scales the ones that are left. The general soft shrinkage rule is defined relation

$$\bar{c}_s(k) = \begin{cases} \text{sign } c(k)\ (|c(k)| - \lambda) & \text{if } |c(k)| > \lambda \\ 0 & \text{if } |c(k)| \leq \lambda \end{cases}$$

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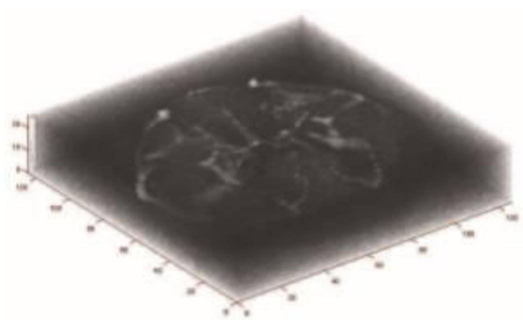
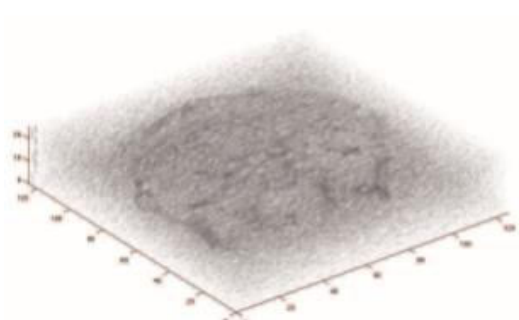
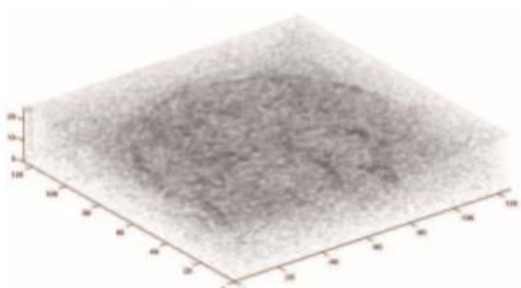
Results of this process applied for a simulated noisy volume processing is presented in Fig. 3. Threshold limits are estimated separately for each subvolume coefficients [30] using a specific algorithm based upon values of wavelet coefficients. Fig. 4 presents the whole process for a selected volume slice starting with the simulated volume and resulting in its reconstruction after the decomposition into the first level. Fig. 5 presents selected first volume slice contours. The compressed LLL subvolume can be used in the next stage to evaluate its 8 subvolumes again.



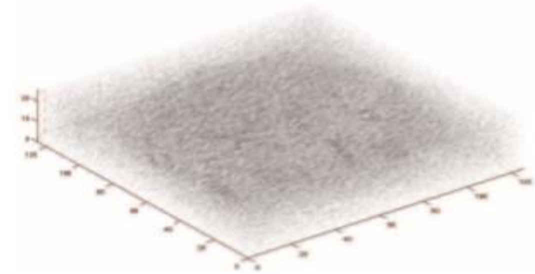
(a) $L^x L^y L^z$.



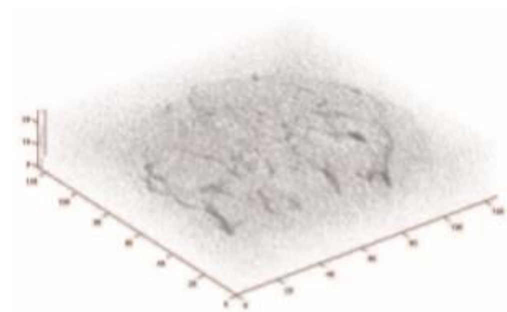
(b) $L^x H^y L^z$.



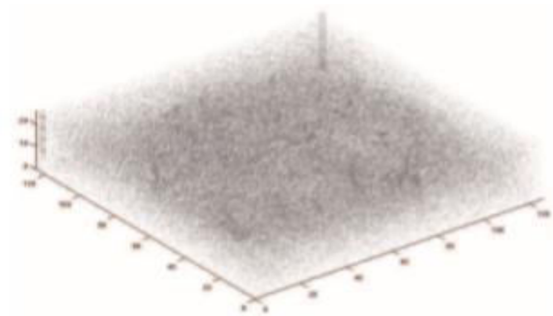
(c) $H^x L^y L^z$.



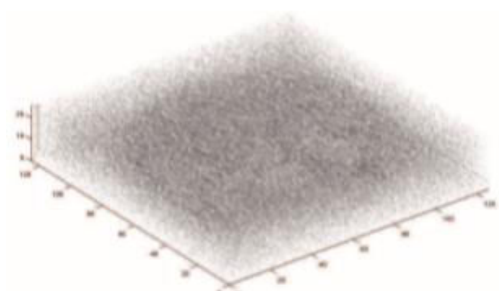
(d) $H^x H^y L^z$.



(e) $L^x L^y H^z$.



(f) $L^x H^y H^z$.



(g) $H^x L^y H^z$.

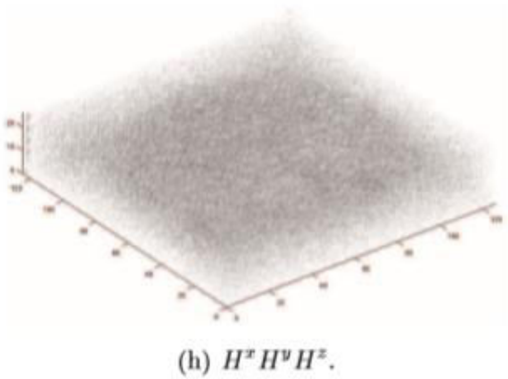
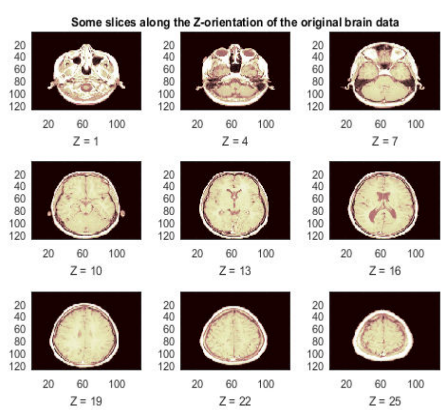
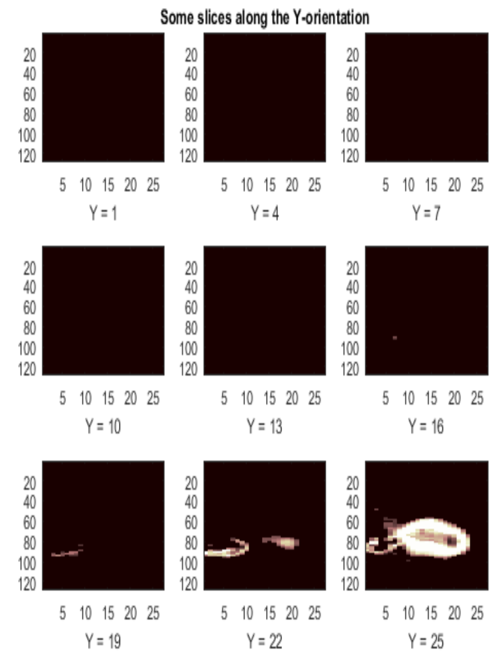


Figure 4.4: Eight octants/subvolumes resulting from the first level 3D sub-sampled wavelet decomposition of the MRI Mouse Brain Vessels volume.

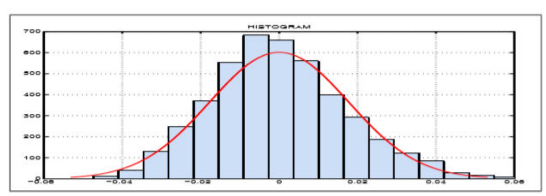
The wavelet decomposition scheme has been applied to the vessel volume for one scale of decomposition. Figure 4.4 shows 8 sub-volumes obtained at the first level of decomposition (1 approximation, 7 details). Each octant has a size divided by 2 compared to the original size of the processed volume. These octants were obtained after one level 3D wavelet transform using the Haar basis, the simplest orthogonal wavelet basis. We can observe that the detail octants show more textures and contours than the low-pass one LxLyLz. The energy (visual vessel filament structures) contained in the low-pass octant is higher than those of high-pass octants. After one scale of decomposition along each direction, the new approximation subband is decomposed further, producing the same number of samples in the subbands than in the original finest resolution image.

Biomedical image processing and volumetric data registration forms an extensive research area with many applications [8, 4, 25, 10, 7, 11, 9, 22]. Fig. 6(a) presents an example of vertebrae volume data used for diagnostical purposes and detection of medical problemsFor classification of volumetric segments it is necessary to find their characteristic





VOLUMECOMPONENTS DETECTION:



Volume components extraction of the vertebrae data from the main processing goal to enable precise diagnosis and treatment. The study is based on fundamental data segmentation.

features. The preliminary studies proved the possibility to use wavelet decomposition again to detect texture complexity and its energy distribution. The following

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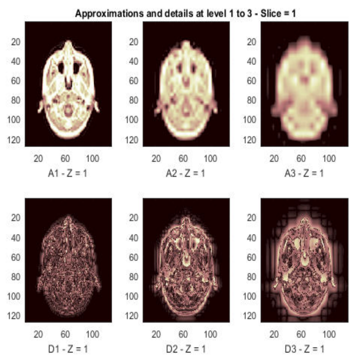
algorithm specify such an approach for each volumetric segment found.

Algorithm B: Feature extraction • Application of the wavelet transform for a selected wavelet and decomposition level • Calculation of the energy inside the image detail subband • Selection of energy components to form the feature vector



Feature vectors can then be classified into the given number of classes using selected clustering methods including neural networks as well.

DISCUSSION:

To study the effect of real data de-nosing the similar noise has been added to real data and the three dimensional wavelet transform with different wavelet functions for volume denoising has been applied using median estimates of threshold values. Further possibilities include their adaptive modification [23]. Fig. 6 compares the vertebrae volume before and after de-noising using db4 wavelet function with contours of the first slice in Fig. 8 allowing numerical comparison of original and processed data. Table 1 presents analysis of the use of different wavelet functions and both local and global thresholding approach. Resulting sum of squared differences between evaluated and original values provides the comparison between selected wavelet functions and presents the efficiency of Haar wavelet function in this case

TABLE-1: Wavelet Function use for MRI data denoising comparing original and reconstructed volumes for different kinds of Thresholding

Method		Error Value		
Thres-holding method	Wavelet function	Set 1	Set 2	Set 3
Local	Haar	0.071	0.079	0.040
Global	Haar	0.063	0.102	0.042

Ongoing work focuses on some examples of 3D medical MRI images that are dealt throughout the thesis: the mouse brain (cerebellum) volume and the vessels of mouse brain volume. As previously described, these obtained MRI models captured during scanning process contain a lot of noise, therefore it is necessary to apply some methods of denoising while almost dynamic geometrical information are preserved. Work of segmenting the mouse brain 3D data (cerebellum) is a difficult issue since the contrast between different objects is low. On the other hand, for the vessels of mouse brain data, biologists want to recover the network of filament structures, especially the small ones inside a noisy volume. We want to know how to recover the real blood-vessels network (without noise). The problem is to identify the noise, since thin structures can be considered as noise as well. Images have to be positioned and oriented relative to one another and aligned exactly so that vessels are continuous through slices. For such volume data, we want to consider medical image processing from the mathematical point of view. Our work is based on two methods: a second-order variational minimization model and the wavelet transform, which applications in image processing are image restoration, segmentation, decomposition strategies and so on. In addition, by considering these methods applied to our noisy MRI images, we can give some conclusions, comparisons, evaluations of advantages/disadvantages of each method. This helps to find the the most appropriate method for dedicated image processing. The principal contributions and conclusions of this work are summarized in the following paragraphs. We have included at the end of each chapter an extended summary and a short discussion of experimental results from the previous chapters is also detailed.

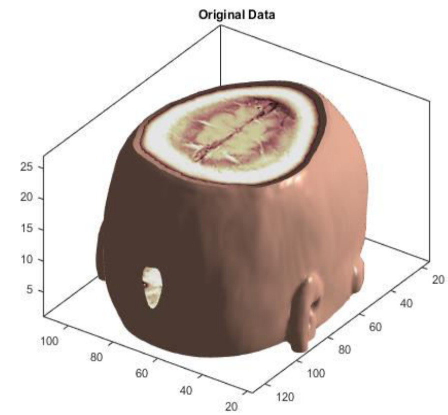
Due to the changing shapes of organs in medical images, segmentation process using multiresolution analysis combined with thresholding as pre- and postprocessing step allows accurate detection of ROIs. Multiresolution analysis such as wavelet transform is extensively used in medical image segmentation and provides better accuracy in results. The future work related to this is the implementation of 3D MRA transform which can be applied directly on medical volumes to detect obstacle and objects of interest.

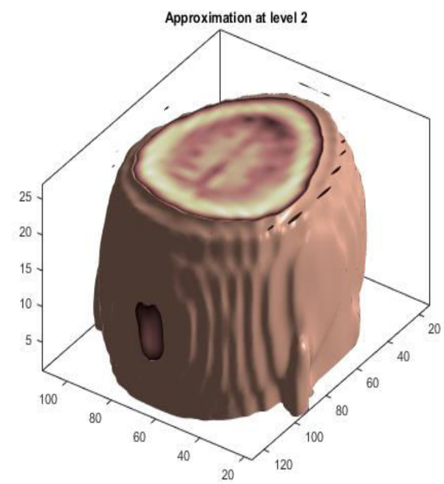
The initial stage of such data processing includes image de-nosing [13, 2, 17] for artifacts rejection. Fig. 7 presents the typical noise analysis using MRI data subvolume selected from area outside the observed body.

RESULTS: The end users of the proposed system are the radiologists and specialists who analyse medical images for cancer diagnosis. After several meetings with those people in the radiology departments in some hospitals, the main goal that they are working is to detect the accurate cancer size in medical images with the least error. This process may be affected by the noise surrounding ROI, which make the process of measuring the exact dimensions of the lesion so hard. Different datasets have been carried out with the proposed system to validate it for clinical applications. The first one is NEMA IEC body phantom which consists of an elliptical water filled cavity with six spherical inserts suspended by plastic rods of inner diameters: 10, 13, 17, 22, 28,and37mm[25,26].Real clinical human images acquired by a CT scanner [24] have also been used to experiment the

proposed approaches, this data has been previously analysed by the radiologists and the provided reports explains that the patients are diagnosed by cancer. Table 1 illustrates the SNR values of extracted features from NEMA IEC DATA SET in spatial domain, different levels of decomposition of wavelet domain and at different block sizes in Wavelet domain. It can be seen fromTable 1 that small values of SNR have been obtained for all techniques; this is due to the noise from the acquisition systems itself. This noise will be a part of the medical image after the reconstruction of all slices. Relatively, better SNR values can be achieved with the second level of wavelet decomposition and as the block size (p) is getting bigger with the Wavelet transform, where the transformed image is getting more similar to the original image. This can be assigned to the major limitation of using Wavelet transformation in medical image segmentation, where ridges rarely exist in such data. MRA transforms have been used with thresholding technique to segment the experimental data. Thresholding technique has been applied as a preprocessing step on the original images at threshold value (t = 35) to remove as much artificially produced from the scanners. The transform then applied to effectively represent objects with edges which are the contours of the medical images followed by another thresholding at (t = 7) to remove most of the remaining noise and facilitate the measurement process. As illustrated in Figure 15, results of the proposed segmentation technique are vary in terms of smooth reconstruction of the spheres. Wavelet transform detect ROI but does not give promising segmentation results due to the lack of ridges or straight lines in the tested data set. Wavelet quadrants are varying also in their quality; relatively, the best results have been achieved with the LL-filter output. ED has been used to measure the spheres diameters and calculate the error percentages for each technique, and sphere diameter error percentages have been calculated as follows:

$$\text{error }\% = \frac{\text{Measured Diameter} - \text{Actual Diameter}}{\text{Actual Diameter}} \times 100\%.$$





CONCLUSION:

The paper forms a contribution to the three-dimensional wavelet transform use for the analysis of the vertebrae volume. The general method of the multi-resolution volume decomposition and reconstruction combined with wavelet coefficients thresholding has been applied for volumetric data de-nosing at first. Volume elements segmentation and classification is mentioned further in connection with wavelet transform use for feature extraction. Resulting algorithms have been used to compare different wavelet functions for rejection of additional noise and proposed methods were then applied for real volumetric data processing to extract their components necessary for a proper analysis, diagnosis and medical treatment. The following work will be devoted to the threedimensional separation of biomedical volume structures to contribute to the more precise detection of anatomic disorders and proposal of their correction using appropriate visualisation methods including the medical virtual reality tools.

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Further mathematical analysis will be devoted to complex wavelet transform use, statistical models, 3D registration, segmentation and visualization in connection with the detail physiological interpretation of results.

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