Brain Tumor Image Edge & Watershed Segmentation and Denoising Using DWT

B.B.S.Kumar, Dr.P.S.Satyanarayana, Rohini G.V

Abstract-Image segmentation is a mechanism used to divide an image into multiple segments. It will make image smooth and easy to evaluate. Segmentation process also helps to find region of interest in a particular image. The main goal is to make image more simple and meaningful. Existing segmentation techniques can't satisfy all type of images.

The scope of the paper is to evaluate the brain tumor image quality edge & watershed segmentation technique by DWT, implemented using MATLAB and simulation carried out on using jpeg image format. To identify tumor from the brain of effected area using edge watershed segmentation then applied to DWT to get good quality image.

This paper introduces an efficient detection of brain tumor from cerebral MRI images. The methodology consists of three steps: edge segmentation, watershed segmentation and denoising by DWT. The Wavelet Transform applied in the segmentation process to decompose MRI image, to find the quality of an image by calculating PSNR and MSE. Some of experimental results on brain image show the feasibility and the performance of the proposed approach.

Index Terms: Peak Signal to Noise Ratio (PNSR), Mean Square Error(MSE), Two Dimensional Discrete Wavelet Transform(2D-DWT), Magnetic Resonance Imaging(MRI).

1 INTRODUCTION

One of the major goal of image processing is to retrieve required information from the given image in a way that it will not effects the other features of that image.

De-noising[15] enhancement of an image is the most important step required to fulfill this requirement. After removing a noise from an image, can perform any operation on that image. Image Segmentation is one of the main steps of image processing, in which any image is being subdivided into multiple segments. Each segment will represent some kind of information to user in the form of color, intensity, or texture. Hence, it is important to isolate the boundaries of any image in the form of its segments. This process of segmentation will assign a single value to each pixel of an image in order to make it easy to differentiate between different regions of any image. This differentiation between different segments of image is done on the basis of three properties of image, i.e., color, intensity, and texture of that image. Therefore the selection of any image segmentation technique is done after observing the problem domain.

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The importance of Image segmentation can't be neglected because it is used in almost every field of science, i.e., removing noise from an image, medical images, satellite imaging, machine vision, computer vision, biometrics, military, Image Retrieval, extracting features and recognizing objects from the given image. It is observed that there is not a perfect method for image segmentation, since each image has its own different type. It is also a very difficult task to find a segmentation technique [1],[2],[3],[4],[6],[8],[10], [11],[13] for a particular type of image. Since a method applied to one image may not remain successful to other type of images, therefore segmentation techniques has been divided into three types, i.e. Segmentation techniques based on classical method, AI techniques, and hybrid techniques. Some of the most famous image segmentation methodologies including Edge and watershed based segmentation, Fuzzy theory based segmentation, Partial Differential Equation (PDE) based segmentation, Artificial Neural Network (ANN) based segmentation, threshold based image segmentation, and Region based image segmentation are highlighted in Fig.(1), contains important and famous image segmentation techniques used for the purpose of image segmentation.

2 LITERATURE SURVEY

Literature survey enables and directs a researcher in the right direction when reviewing the previous publications. Review papers provide the loop holes of previous and existing systems the work to be carried out to apply a correct methodology to move forward a researcher. The literature survey helps proving and disproving of any work.

Many papers where reviewed on image segmentation using DWT[34],[36],[37],[38], it is found that demerits in the previous existing method. This has encouraged carrying out this project to finding out of an image quality using PSNR and MSE[1],[38].

3 MOTIVATION

Image registration, enhancement, compression & de-noising, restoration and segmentation are the versatile techniques which are used in image processing. The important process is image reconstruction and retrieving image at the reception. The goal of image processing is to obtain without loss information from the image content retrieving. Using any algorithms to implement and better resolution of an image from the any transmission channel. So this has been motivated me to carry on image segmentation techniques of medical images retrieving without loss of information.

4 EXISTING METHOD

From referring previous papers[1],[3],[4],[5],[28] to implement image segmentation have used algorithms like Local Histogram Range Image method, K-Means Clustering, Otsu's adaptive thresholding, edge detection, watershed and wavelets. There are many drawbacks in implementing previous algorithms by using inter related methods have not achieved better results, to identify the brain tumor of edges, contour, intensity levels, energy levels and retrieving image.

5 DWT

The Wavelet technique[35] is age old signal processing method, it is a mathematical representation or expression having the data. So discrete wavelet transform is derived from FT (Fourier Transform), STFT (Short Time Fourier Transform), FFT (Fast Fourier Transform), DFT (Discrete Fourier Transform), and CWT (Continuous Wavelet Transform). The wavelets having advantage over Fourier transform because the image can be represented in both frequency attributes of characteristics and spatial domain but Fourier transform can be represent only in frequency attributes of an image.

Wavelets having the properties scalability, translatability, multi resolution compatibility and orthogonality. Wavelets provides better resolution of an image for pre processing and post processing technique.

- Provides sufficient information both for analysis and synthesis
- Reduce the computation time sufficiently
- Easier to implement
- Analyze the signal at different frequency bands with different resolutions
- Decompose the signal into a coarse approximation and detail information

5.1 Wavelet Transform

- Provides time-frequency representation
- Wavelet transform decomposes a signal into a set of basis functions (wavelets)
- Wavelets are obtained from a single prototype wavelet $\Psi(t)$ called mother wavelet by dilations and shifting:

  $\Psi_{a,b}(t) = (1/\sqrt{a})\, \Psi(t-b)/a$ (1)

  – where **a** is the scaling parameter and **b** is the shifting parameter
- Wavelet analysis produces a *time-scale* view of the signal.
  – *Scaling* means stretching or compressing of the signal.

5.2 The Good Transform Should be

- Decorrelate the image pixels
- Provide good energy compaction
- Desirable to be orthogonal

5.3 2-D DWT Processing

Step 1: Replace each row with its 1-D DWT.
Step 2: Replace each column with its 1-D DWT
Step 3: Repeat steps 1 & 2 on the lowest subband for the next scale.
Step 4: Repeat step 3 until as many scales as desired

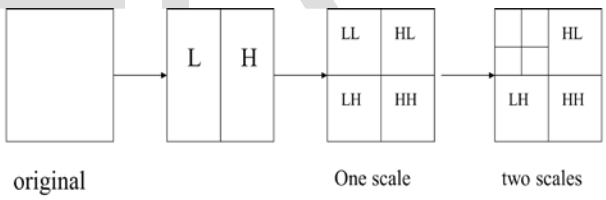

Fig.1.Subband Scaling

6 MEDICAL IMAGING

Medical imaging is the technique, process and art of creating visual representations of the interior of a body for clinical analysis and medical intervention. Medical imaging seeks to reveal internal structures hidden by the skin and bones, as well as to diagnose and treat disease. Medical imaging also establishes a database of normal anatomy and physiology to make it possible to identify abnormalities. Although imaging of removed organs and tissues can be performed for medical reasons, such procedures are usually considered part of pathology instead of medical imaging.

As a discipline and in its widest sense, it is part of biological imaging and incorporates radiology which uses the imaging technologies of X-ray radiography, magnetic resonance imaging, medical ultrasonography or ultrasound[12], endoscopy, elastography, tactile imaging, thermography, medical photography and nuclear medicine functional imaging techniques as positron emission tomography. Magnetoencephalography (MEG), Electroencephalography (EEG), Electrocardiography (ECG), and others represent other technologies which produce data susceptible to representation as a parameter graph *vs.* time or maps which contain information about the measurement locations. Measurement and recording techniques which are not primarily designed to produce images. In a limited comparison these technologies can be considered as forms of medical imaging in another discipline.

Up until 2010, 5 billion medical imaging studies had been conducted worldwide. Radiation exposure from medical imaging in 2006 made up about 50% of total ionizing radiation exposure in the United States.

In the clinical context, "invisible light" medical imaging is generally equated to radiology or "clinical imaging" and the medical practitioner responsible for interpreting (and sometimes acquiring) the images is a radiologist. "Visible light" medical imaging involves digital video or still pictures that can be seen without special equipment. Dermatology and wound care are two modalities that use visible light imagery. Diagnostic radiography designates the technical aspects of medical imaging and in particular the acquisition of medical images. The radiographer or radiologic technologist is usually responsible for acquiring medical images of diagnostic quality, although some radiological interventions are performed by radiologists. While radiology is an evaluation of anatomy, nuclear medicine provides functional assessment.

As a field of scientific investigation, medical imaging constitutes a sub-discipline of biomedical engineering, medical physics or medicine depending on the context: Research and development in the area of instrumentation, image acquisition (e.g. radiography), modeling and quantification are usually the preserve of biomedical engineering, medical physics, and computer science; Research into the application and interpretation of medical images is usually the preserve of radiology and the medical sub-discipline relevant to medical condition or area of medical science (neuroscience, cardiology, psychiatry, psychology, etc.) under investigation. Many of the techniques developed for medical imaging also have scientific and industrial applications.

Medical imaging is often perceived to designate the set of techniques that noninvasively produce images of the internal aspect of the body. In this restricted sense, medical imaging can be seen as the solution of mathematical inverse problems. This means that cause (the properties of living tissue) is inferred from effect (the observed signal). In the case of medical ultrasonography, the probe consists of ultrasonic pressure waves and echoes that go inside the tissue to show the internal structure. In the case of projectional radiography, the probe uses X-ray radiation, which is absorbed at different rates by different tissue types such as bone, muscle and fat.

The term noninvasive is used to denote a procedure where no instrument is introduced into a patient's body which is the case for most imaging techniques used.

7 A BRAIN MRI REPRESENTATION

7.1 Brain Tumor

A brain tumor[4],[5] is an abnormal growth of tissue in the brain. Unlike other tumors, brain tumors spread by local extension and rarely metastasize (spread) outside the brain. A benign brain tumor is composed of non-cancerous cells and does not metastasize beyond the part of the brain where it originates. A brain tumor is considered malignant if it contains cancer cells, or if it is composed of harmless cells located in an area where it suppresses one or more vital functions.

7.2 MRI Representation

A Magnetic Resonance Imaging instrument (MRI scanner), or "Nuclear Magnetic Resonance (NMR) imaging" scanner as it was originally known, uses powerful magnets to polarise and excite hydrogen nuclei (single proton) in water molecules in human tissue, producing a detectable signal which is spatially encoded, resulting in images of the body. The MRI machine emits a RF (Radio Frequency) pulse that specifically binds to hydrogen. The system sends the pulse to the area of the body to be examined. The pulse makes the protons in that area absorb the energy needed to make them spin in a different direction. This is the "resonance" part of MRI. The RF pulse makes them (only the one or two extra unmatched protons per million) spin at a specific frequency, in a specific direction. The particular frequency of resonance is called the Larmour frequency and is calculated based on the particular tissue being imaged and the strength of the main magnetic field. MRI uses three electromagnetic fields: a very strong (on the order of units of teslas) static magnetic field to polarize the hydrogen nuclei, called the static field; a weaker time-varying (on the order of 1 kHz) field(s) for spatial encoding, called the gradient field(s); and a weak RF field for manipulation of the hydrogen nuclei to produce measurable signals, collected through an RF antenna.

Like CT(Computed Tomography), MRI traditionally creates a two dimensional image of a thin "slice" of the body and is therefore considered a tomographic imaging technique. Modern MRI instruments are capable of producing images in the form of 3D blocks, which may be considered a generalization of the single-slice, tomographic, concept. Unlike CT, MRI does not involve the use of ionizing radiation and is therefore not associated with the same health hazards. For example, because MRI has only been in use since the early 1980s, there are no known long-term effects of exposure to strong static fields (this is the subject of some debate; see 'Safety' in MRI) and therefore there is no limit to the number of scans to which an individual can be subjected, in contrast with X-ray and CT. However, there are well-identified health risks associated with tissue heating from exposure to the RF field and the presence of implanted devices in the body, such as pace makers. These risks are strictly controlled as part of the design of the instrument and the scanning protocols used.

Because CT and MRI are sensitive to different tissue properties, the appearance of the images obtained with the two techniques differ markedly. In CT, X-rays must be blocked by some form of dense tissue to create an image, so the image quality when looking at soft tissues will be poor. In MRI, while any nucleus with a net nuclear spin can be used, the proton of the hydrogen atom remains the most widely used, especially in the clinical setting, because it is so ubiquitous and returns a large signal. This nucleus, present in water molecules, allows the excellent soft-tissue contrast achievable with MRI.

8 SEGMENTATION

8.1 Edge Based Image Segmentation

Edge detection is a basic step for image segmentation [1],[3] process. It divides an image into object and its background. Edge detection divides the image by observing the change in intensity or pixels of an image. Gray histogram and Gradient are two main methods for edge detection for image segmentation. Several operators are used by edge detection method, i.e., Classical edge detectors, zero crossing, Laplacian of Guassian (LoG), and color edge detectors etc.

8.2 Watershed Transformation Image Segmentation

The watershed[13] transformation considers the gradient magnitude of an image as a topographic surface. Pixels having the highest gradient magnitude intensities (GMIs) correspond to watershed lines, which represent the region boundaries. Water placed on any pixel enclosed by a common watershed line flows downhill to a common Local Intensity Minimum (LIM). Pixels draining to a common minimum form a catch basin, which represents a segment.

9 PROPOSED METHOD

9.1 Detecting a Brain tumor Using Image Segmentation

An object can be easily detected in an image if the object has sufficient contrast from the background. Using edge detection and basic morphology tools to detect a prostate brain tumor.

Step 1: Read Image
Step 2: Detect Entire Brain Tumor
Step 3: Dilate the Image
Step 4: Fill Interior Gaps
Step 5: Remove Connected Objects on Border
Step 6: Smoothen the Object
Step 7: Apply Watershed Transformation Image Segmentation
Step 7: Apply PSNR & MSE
Step 8: For Segmented Image apply the DWT

9.2 Simulations Tools Used

This project is implemented using Matlab 2012b. All the experimental results tested and carried out on simulation only using medical MRI image jpeg image format, dimensions 448 x 448, gray scale.

9.3 Watershed Segmentation Algorithms

Segmentation using the watershed transform [8], [13], works better if you can identify, or "mark," foreground objects and background locations. Marker-controlled watershed segmentation follows this basic procedure:

- Compute a segmentation function. This is an image whose dark regions are the objects you are trying to segment.
- Compute foreground markers. These are connected blobs of pixels within each of the objects.
- Compute background markers. These are pixels that are not part of any object.
- Modify the segmentation function so that it only has minima at the foreground and back ground marker locations.
- Compute the watershed transform of the modified segmentation function.

9.4 Image De-noising Algorithms

Step 1: Start
Step 2: DWT compressed image is applied to IWT and set threshold value and wavelet
Step 3: Call the function of De-noising[28] and set threshold values, results in reconstructed (de-noised) image
Step 4: Evaluate PSNR and MSE for original image and de-noised image
Step 5: Repeat the same process for different threshold values and wavelet
Step 6: End of the process

9.5 PSNR(Peak Signal to Noise Ratio)

The following equation defines the PSNR:

$$20\log_{10}(2^{B}-1)/\sqrt{MSE} \quad (2)$$

where *MSE* represents the mean square error and *B* represents the bits per sample.

9.6 MSE(Mean Square Error)

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The mean square error between a signal or image, X, and an approximation, Y, is the squared norm of the difference divided by the number of elements in the signal or image:

$$(\|X-Y\|^2)/N \quad (3)$$

10 EXPERIMENTAL RESULTS

The experiments is carried out on jpeg image format, it is lossy compression technique. The objective of project is:

- Edge Segmentation
- Smoothening the image
- Watershed transformation image segmentation to identifying the tumor
- Applying the DWT to denoise[34],[38] the image

The images are taken from MRI image from the hospital. Using segmentation can be identified tumor in the brain. Then applying DWT the segmented image can be multi resolute to have a good quality image.

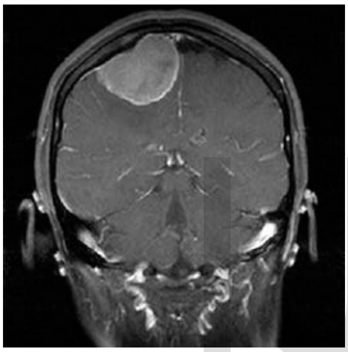


Fig.1.Original Image 448x448, gray scale

10.1 Edge Image Segmentation

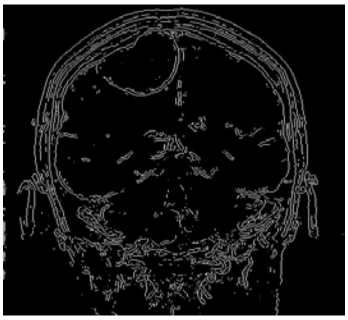


Fig.2.Binary Gradient Mask

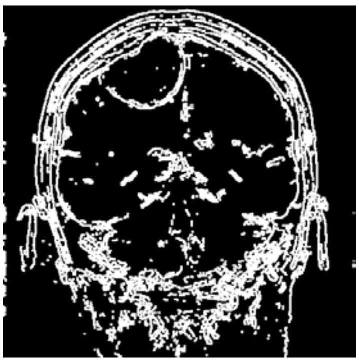


Fig.3.Dilated Gradient Mask

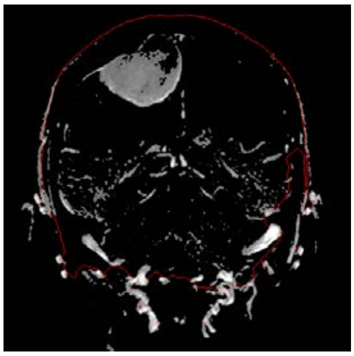


Fig.4.Outlined Original Image

10.2 Watershed Image Segmentation

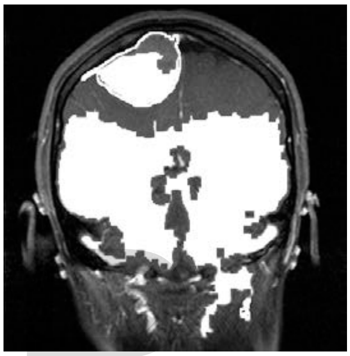


Fig.5.Modified regional maxima superimposed on original image

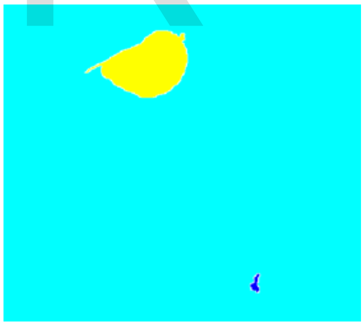


Fig.6.Colored Watershed Label Matrix

Edge segmentation helps to find the edges of affected area and removes the unwanted data. From the watershed method separates the spot from the other tissues in the brain. By using both the methods image quality is improved and provides better analysis to identify the brain tumor.

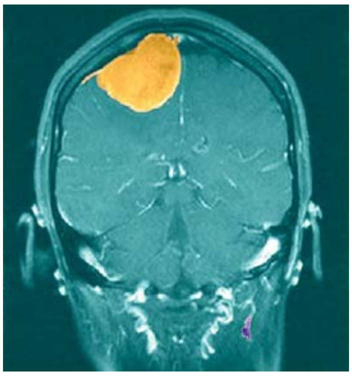


Fig.7. Superimposed Transparently on Original Image

10.3 2-D DWT Decomposition

In the discrete wavelet transform[32], an image signal can be analyzed by passing it through an analysis filter bank followed by a decimation operation. This analysis filter bank, which consists of a low pass and a high pass filter at each decomposition stage, is commonly used in image compression. When a signal passes through these filters, it is split into two bands. The low pass filter, which corresponds to an averaging operation, extracts the coarse information of the signal. The high pass filter, which corresponds to a differencing operation, extracts the detail information of the signal. The output of the filtering operations is then decimated by two. A two-dimensional transform Fig.(7), can be accomplished by performing two separate one-dimensional transforms. First, the image is filtered along the x-dimension and decimated by two. Then, it is followed by filtering the sub-image along the y-dimension and decimated by two. Finally, we have split the image into four bands denoted by LL, HL, LH and HH after one-level decomposition Fig.(9a). Further decompositions can be achieved by acting upon the LL subband successively and the resultant image is split into multiple bands as shown in Fig.(9b) & Fig.(9c), the synthesized image as shown in Fig.(9d).

10.4 Algorithm For Decomposition

Step 1: Start-Load the source image data from a file into an array.
Step 2: Choose a Biorthogonal Wavelet.
Step 3: Decompose-choose a level **N**, compute the wavelet decomposition of the signals at level **N**.
Step 4: Compute the DWT of the data.
Step 5: Read the 2-D decomposed image to a matrix.
Step 6: Retrieve the low pass filter from the list based on the wavelet type.
Step 7: Compute the high pass filter **i=1**.
Step 8: **i >= 1**decomposed level, then if Yes goto step 10, otherwise if No go to step 9.
Step 9: Perform 2-D decomposition on the image **i++** and goto to step 8.
Step 10: Decomposed image.
Step 11: End.

10.5 Algorithm for Reconstruction

Step 1: Start-Load the source image data from a file into an array.
Step 2: Choose a Biorthogonal Wavelet.
Step 3: Decompose-choose a level N, compute the wavelet Decomposition of the signals at level N.
Step 4: Compute the DWT of the data.
Step 5: Read the 2-D decomposed image to a matrix.
Step 6: Retrieve the low pass filter from the list based on the wavelet type.
Step 7: Compute the high pass filter i=decomp level.
Step 8: i <= 1, then if Yes goto step 10, otherwise if No goto step 9.
Step 9: Perform 2-D reconstruction on the image and goto to step 8.
Step 10: Reconstruction image.
Step 11: End.

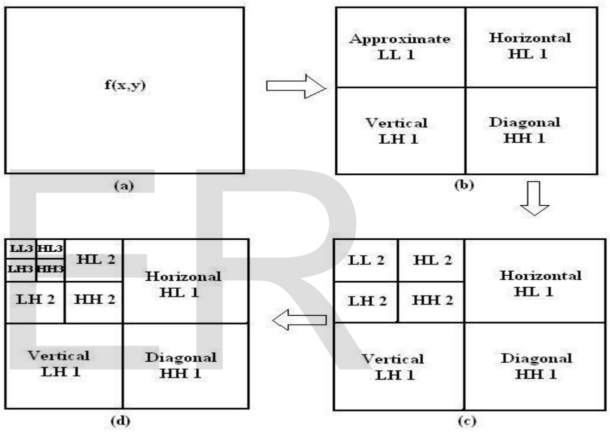
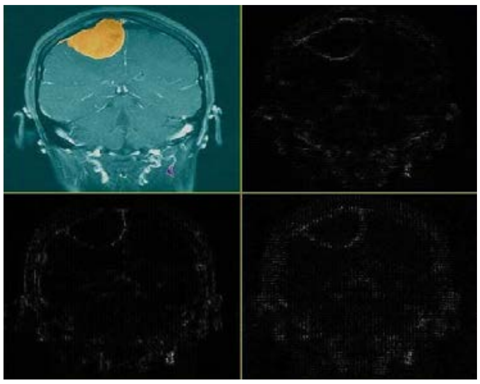


Fig.8. DWT Decomposition: a) Original Image b) One Level Decomposition c) Two Levels Decomposition. D) Three Levels Decomposition.



(a)

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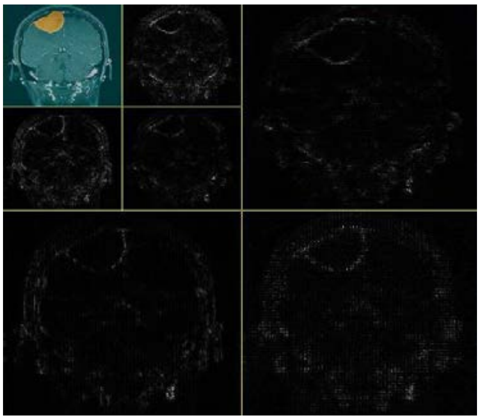
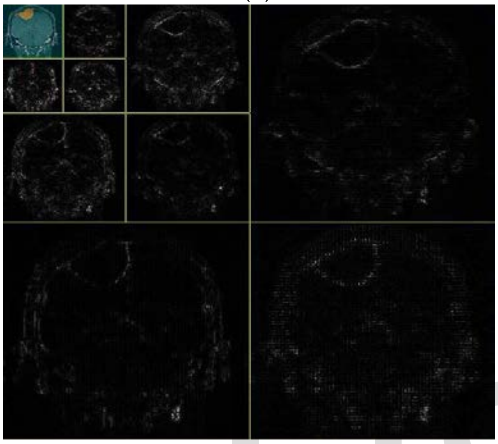
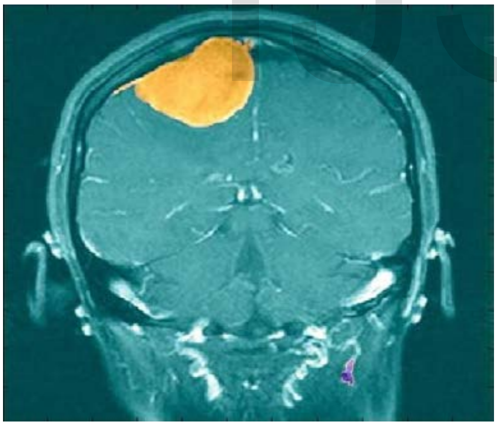


(b)



(c)



(d)

Fig.9. Decomposition Approximations: (a) Decomposition Level 1 (b) Decomposition Level 2 (c) Decomposition Level 3 (d) Synthesized Image

10.6 Denoising

Applying bi-orthogonal(bior3.9) wavelet, jpeg synthesized image 545 x 545, Decomposition level-2, soft thresholding - 5, Selected thresholding method fixed form. Selected noised structure[22],[23],[29],[30],[31],[33] unscaled white noise & horizontal details coefficient.

Image	PSNR	MSE
Original	13.9104	2.6426e+03
Segmented	14.7862	2.1601e+03
Reconstructed bior3.9 Decomposition level-2	14.7124	2.1971e+03
Denoised Image	14.7942	2.1561e+03

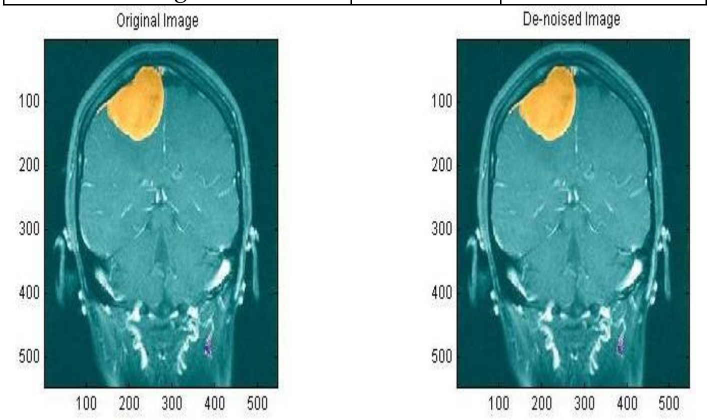


Fig.10.Denoised image

10.7 PSNR & MSE

Table 1
PSNR & MSE

From the above Table.(1) shows the image quality improvement from the image segmentation and denoising by using DWT. The original image differs in the clarity and PSNR value low comparing with segmentation & denoising images. The segmented, reconstructed and denoised image having improved quality but differ in PSNR value, denoised image by using biorthogonal (bior3.9) wavelet having better results higher PSNR value. If PSNR value lower than the MSE than image quality is poor, always PSNR value should be higher than the MSE value to have good quality image.

11 CONCLUSION

In this paper, techniques of edge & watershed image segmentation is implemented, an overview related image segmentation technique has been presented in this paper. The objective of research work is to identify edges of tumor by edge segmentation and the tumor exact spot by watershed segmentation method, and also to improve the image quality by denoising. The segmented image is decomposed and denoised by DWT. It is a challenging task in the medical images information should not be lost. This paper achieved improved results in the image quality when segmented image is denoised, after segmentation and denoising PSNR having higher & lower MSE value.

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