An efficient segmentation System for Alzhiemer's Disease Detection from Magnetic Resonance Imaging using TDWT – Fuzzyset Theory

Chithra. S[1]

Research Scholar, Department of Computer Science, Avinashlingam Institute for Home Science and Higher Education for Women, Coimbatore, Assistant Professor, Department of Computer Science, Krupanidhi Degree College, Bengaluru, India, chithra.kdc@gmail.com

R.Vijayabhanu[2]

Assistant Professor, Department of Computer Science, Avinashilingam Institute for Home science and Higher Education for Women,Coimbatore, India, vijayabhanu.R@gmail.com

Abstract:

The neural system of Brain will help to exchange the information throughout the anatomical structure of human body. Alzheimer's disease (AD) is a progressive form of dementia that is caused by a monogenic accumulative condition that mostly impacts memory function in the human brain. Using MRI as the primary research tool, the primary objective of this work is to locate and categorize Alzheimer's disease biomarkers. Two different adaptive filtering strategies are utilized in order to eliminate the noise in MRI scans. In order to detect the segmentation of the Alzheimer's disease affected region, the TDWT-Fuzzy Set Theory has been proposed as a method. The Alzheimer's disease Neuroimaging Initiative (ADNI) database was used to evaluate the approach. This database has one hundred different datasets. The collection of data includes T1-weighted MR images in the sagittal plane, comprising 40 normal samples, 40 MCI samples, and 20 AD samples. There are 51 female samples and 49 male samples total. Their ages range anywhere from 57 to 95 years, with the average being 95. To remove the noise of MRI images of AD, the Hampel Identifier, Adaptive median filter and proposed method are used. The proposed method shows that better results when compared to the other images with (30%, 40% and 50%). The proposed segmentation algorithms performance evaluation of PSNR, SNR, MSE and MAE shows more than 53% than compared with Threshold, Region growing. When compared to previous image segmentation techniques, the suggested method performs better at identifying areas that are afflicted by Alzheimer's disease.

Keywords: Alzheimer's disease, DWT, Fuzzy set, Threshold, Region growing, Segmentation.

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1. Introduction

AD stage analysis plays a significant role in patient care also further treatment process in recent times. Detecting AD from MCI (Mild Cognitive Impairment) and CN (Cognitive Normal) has grown into popular. AD builds a loss of association among nerve cells in elder peoples so that is identified as is a liberal dementia. The patient brain shrinks, hippocampal size reductions and the brain ventricles expand are occurred due to AD disease. In day-to-day activities, AD degrades memory power, thinking capability also changes in person's expressions. Computer aided diagnosis techniques in medical scan images are used to classify the AD stages accurately that will helpful for physicians to provide the proper treatment [1].

One of the most crucial aspects of clinical diagnosis as well as the succeeding stages of image processing that are included in medical image processing is segmentation. The accurate diagnosis of Alzheimer's disease is a procedure that is not only challenging but also time-

consuming, and it does not guarantee accurate results even when performed by a professional 'pathologist'. As a result, the development of the most effective approaches that enable the automatic segmentation of digital MRI images impacted by Alzheimer's disease is an absolute necessity. In this study paper, the segmentation system architectures that were used are presented in figure 1.

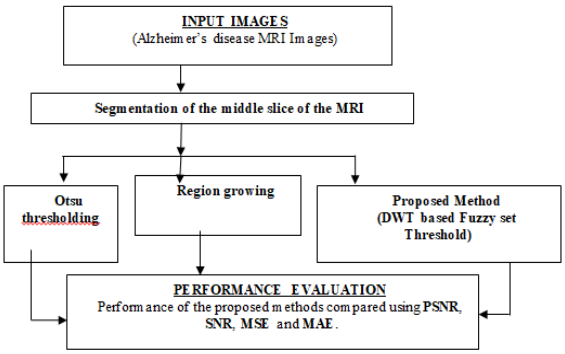

Figure.1 System Architecture

The Seed-Based Region Growing (SBRG) technique was proposed by Shafaf Ibrahim et al. in 2017, and it was based on the general agreement among radiologists and radiographers. It has been determined that this particular approach of skull stripping is extremely effective [2].

An automatic approach for removing artifacts and the skull from brain MRI scans was developed by Sudipta Roy and colleagues in 2017 [3]. The researchers broke their method down into many stages, using computational geometry, wavelet decomposition, and thresholding as the several intermediate steps along the way.

Yasmeen et al., (2021) developed the hybrid watermarking system that is applied in digital input data to provide the strength and security. This proposed hybrid technique is a form of DWT and SVD. The implanting and features extraction methods are carried out over multi-level processes of DWT and then SVD [4].

Ismail Yaqub Maolood et al., (2018) presented a novel method for cancer picture segmentation by combining fuzzy entropy with a level set thresholding system. This technique was successful in identifying cancerous areas. This method was successfully implemented in a variety of imaging applications, including MRI, ultrasound, breast cancer, and dermoscopy images of the skin. Additionally, the effectiveness of the suggested strategy is evaluated by contrasting the findings obtained using various algorithms from previous research. [5].

2. Preliminary Views

2.1 Magnetic Resonance Imaging

The MRI is an intraoperative diagnosing system in medical imaging, which is operate in radiology to envisage the internal structure as well human body functionalities. Especially, it is operated in oncological (cancer), neurological (brain), and heart functionalities imaging. At this point an unsurpassed magnetic portion, a radio frequency pulse as well as computer systems are operated to produce in depth picture of human organs, soft tissues, bones plus other internal part structures. The customary/usual MRI scan system is a large tube, which is cylindrically molded enclosed in a round magnet objects. Nothing like CT (Computed Tomography) imaging scans also predictable X-rays but MRI does not abuse ionizing radiation power. A great magnetic field will support the nuclear attracting of hydrogen atoms of water in the human body, whereas the patient is in the imaging scanner without producing any chemical reaction in the human body. Some energy will be released in the form of hydrogen atoms that will reoccurrence to their normal position, which will have based on the type of human body tissue. This power/energy will be taken by using the MRI scanner then make the image of scanned tissue depend on the facts [6]. Earlier days the MRI is called as N-MRI.

2.2 Segmentation

In medical image processing, segmentation of the object is the keystone in quantitative analysis and the basis of registration that is also called as reconstruction. Segmentation of objects in MR images plays an important role in clinical and research applications [7]. It is very difficult for quantitative analysis of medical images because of their complex texture and fuzzy edge. Consequently, the performance comparisons of these approaches would be essential. This research proposed a novel segmentation method that is Discrete Wavelet transform (DWT) based Fuzzy Set Threshold method.

2.2.1 Threshold Based Segmentation

In medical image analysis, segmentation of objects by utilizing threshold method is a simple however really powerful technique based on input image space area i.e. properties of the input image. Typically, this kind of process is applied in input images that consuming a light object on a darker background or else vice versa.

An appropriate threshold value is chosen to separate image's pixels into certain classes as well as split objects from the background by using thresholding algorithm. From the input image, pixel (x, y) for that f(x, y)>=T is measured to be focal point whereas any pixel (x, y) that has value f(x, y) <T is measured to be image background [8].

The global thresholding technique is developed when the intensity sharing among the items of the foreground and backgrounds are extremely different from one another, and a single value of the threshold may simply be used to differentiate both of the objects individually. Accordingly, the value of threshold T base exclusively on the properties of the pixel and the grey level value of the image. Most generally utilized global thresholding methods are the entropy-based thresholding, Otsu method and so on.

The Otsu has a lot of drawbacks, but the most significant one is that the precision of the thresholds required for it to work properly decreases as the number of segments that need to be separated increases.

2.2.2 Region Growing (RG) Segmentation

RG is a method for digital picture segmentation that relies on selecting primary seed points in addition to adding nearby pixels into the region based on some criteria, such as colour similarity or intensity value. This method is dependent on choosing primary seed points. By employing this approach, a given image can have its pixels easily divided into two distinct zones, such as the background and the foreground. The RG method suggested a simple way to pick an initial seed and then expand it. In this algorithm, let x$\in \boldsymbol{I}$ be an arbitrarily chosen pixel in an input two dimensional digital image I. Let R_f is a ROI (Region Of Interest) of the input image I, i.e. foreground and $\delta_1$is acceptance of the variance in intensity value. An easy method to enlarge R_f is to compare every adjacent pixels with the primary seed also allocate all pixel to $R_f$if it fulfills

$$|x - N(p)| \leq \delta_1$$

Where is a adjacent/ neigborhood pixel of $N(p) \in \boldsymbol{I}$ then it is the absolute of the variance of intensity. Once a pixel is allocated to R_f, the fresh adjacent pixel can be estimated in the similar way. Inappropriately, the result will lead to an undesirable result once a noise pixel is selected. Alternative method is to compare the pixel at the furthest region with the nearby adjacent pixel to overcome this problem that is similar to above mentioned equation however the comparison is among $N(p)$ also furthest pixel of R_f, viz. $S(x)$

$$|S(x) - N(p)| \leq \delta_1$$

The main method leads to reliable segmented areas however it is very complex to noise though the next method may result in inexact image segmentations mainly in cases where the input pixel characteristics modification slowly, and then it is strong to noise [9].

Many seeds can be an unusual to solve the above issue. The initialization process cannot start with the single pixel however a small group of pixels to superior describe the region using arithmetical tools like mean or variance. Then the development also includes a statistic process and this is an exclusive process for each nearby pixel is evaluated not as a particular pixel but as an area [9].

Algorithm:

STEP 1: Read input (MRI) image $'I'$.

STEP 2: Pick the seed pixel, which is represented by x, from the input image $'I'$

STEP 3: Check the adjoining image pixels $'N(p)'$ add them to the $'R_f$ when they are same to the seed

STEP 4: Repeat 'step2' for every of the freshly inserted pixels; that is terminated once no more pixels can be available to insert.

Drawbacks

- The seed point needs to be supplied right from the beginning for the sensitive initialization process to take place. Images can either be under-segmented or over-segmented if an incorrect initial seed point is chosen.
- When utilizing the RG algorithm, FEIs can often be forced to endure with limited resolution, decreased contrast, and speckle noise. This can lead to disjointness as well as ambiguity in the segmented boundaries.

The time required for computation is rather lengthy, and it is not suitable for use with noisy data.

3. Proposed System

The ultimate aim of the proposed system is to accurately segment the middle slice of the brain without loss of fine details of the AD-MRI images. Several models were available for segment of object in MRI but the proposed model is considered to be more efficient since it integrates the with the threshold system. The proposed algorithms' operational mechanisms are depicted in figure below.

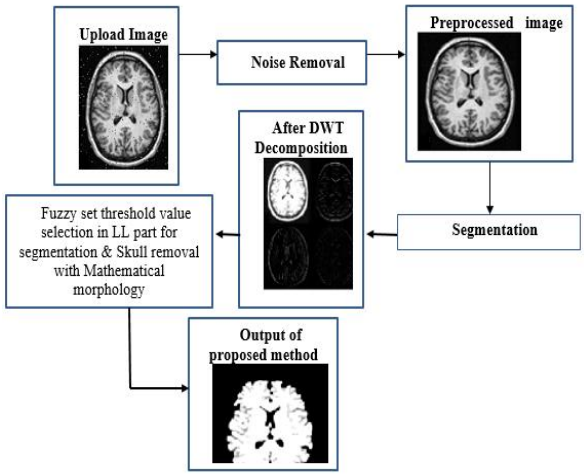

Figure.2. Proposed System Architecture

3.1 Noise and Artifact Removal

The storing and recording of signals is essential to the operation of an MRI system. These signals are frequency encoded through the application of incline fields in 3 different orthogonal ways. The application of an inclination in a homogeneous part creates a linear variation, which is necessary for the creation of spatial encoding.

Therefore, the spatio-frequential relationship is linear in a magnetic field with the same characteristics for each spatial coordinate of the volume that was analyzed, which mimics a single frequency synchronize. Errors in the spatial encoding cause artifacts and sounds to be produced if a magnetic susceptibility with a high value is put inside of a magnetic field. [10]. Lot of filtering techniques are applied in existing researcher to remove the noise in medical images. But this paper primarily emphasis on how to eliminate the noise and random valued artifacts without removing fine details.

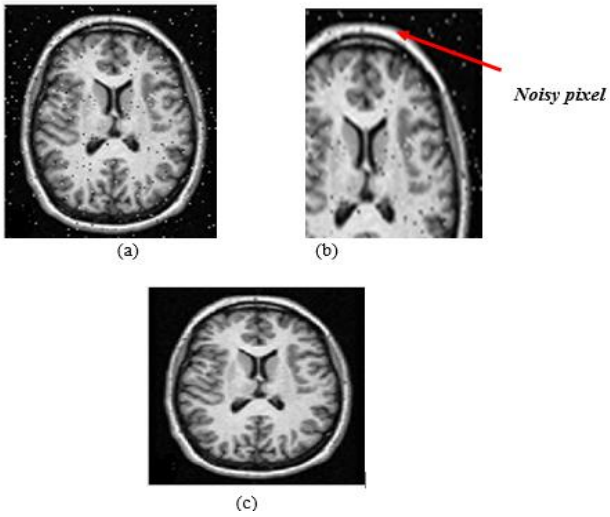

Figure.3. (a) An example of an image with noise; (b) a zoomed-in view of a noise pixel; and (c) an example of an image with no noise.

In this work, an Adaptive Hampel Identifier (AHI) noise removal technique is proposed for effective noise as well as artifacts elimination. The HI is a conventional one, and it consists of simply deliberate forwards then backwards image data of the current position. The observation, on the other hand, is only in two dimensions. It should come as no surprise that it was derived from the idea of using the identify window to go from 1D to 2D in an image processing system [11]. The proposed algorithm is described below,

1. *Start*
2. *Determine the median and the standard deviation of the median.*

3. Determine the value that constitutes the adaptive rejection threshold

4. Determine the state of the current pixel using the adaptive threshold

5. Replace the faulty pixel with the one just adjacent to it

6. End

The methods which are adopted to compare with proposed as: Hampel identifier and Adaptive median filter.

3.2 Discrete Wavelet Transform (DWT):

In recent years, DWT is generally utilized mathematical tools that can extract data from input image efficiently. In this research paper, the principle strategy of DWT is utilized to divide/decompose the histogram of 2D-image in multi-scale way. Initially, the approximate of threshold value is found in large scale manner and then the scale is slowly diminished to segment the object accurately using threshold value. The object segmentation technique depends on DWT can efficiently evade the effect of noise [12]. The primary idea of the proposed approach is that the input MRI image is decomposed into various levels of wavelet coefficients.

In an input MRI image, the low frequency part gives global explanation as well as the high frequency part gives data about better details. The high scale as well as low frequency scale of the image components are achieved with filtering process in wavelet analysis. An input image is sub-sampled into various sub-bands depend on its spatial as well as frequency modules. In wavelet transform, the input pictures are processed via both a high pass filter and a low pass filter before being decomposed into two distinct versions, referred to as the low pass-L version and the high pass-H version, respectively. After that, a set of low pass (LL), high pass (LH), low pass (HL), and high pass (HH) filters are manufactured by once again decomposing the low pass version and the high pass version. It is possible to continue processing this approach until an input medical image has been deconstructed to a previously determined reference level.

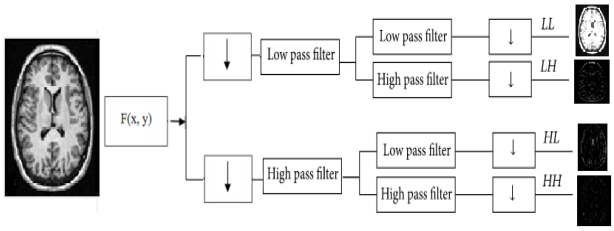

Figure.4.DWT processing structure

The fig.4 demonstrates that four various sub bands images for example LL, LH, HL and HH bands which is decomposed from original input image. From that, LH sub band image is very sensitive to differences in expression, HH sub band image is highly sensitive to noise and HL sub band image differ with variations in the position. Based on the wavelet type, DWT can be categorized into different forms. Wavelet is based on decomposition filters and arbitrary molded waveform cannot utilized wavelet function. Haar, Symlet, Bi-orthogonal and Reverse Bi-orthogonal are few primary kinds of wavelets. In this research, Haar based wavelet is used for decomposition process.

The original image is convolved along for compute DWT for a 2D input image (F(x, y)) and the directions of high pass as well as low pass filters are shown in Fig.4. In the output images, ↓ indicates the down sampled columns which means only even indexed columns are chosen. After this, the resulting images are processed once more through low pass and high pass filters. After convolution, those images are again down sampled with rows and denoted by ↓ that ultimately yields four sub band images, which is partial in original input image. In the end, several distinct sorts of sub band images are created, specifically LL, LH, HL, and HH images. LH, HL, and HH are abbreviations that stand for the image's horizontal, vertical, and diagonal information, correspondingly. As a result, the four sub band pictures that are produced are denoted by the letters LL, LH, HL, and HH. LH, HL, and HH each carry information on the input image's horizontal, vertical, and diagonal details, respectively. If the input image has 2k elements in either the column or row, then the wavelet transform constants for low pass as well as high pass will be constructed subsequently each step of the filtering procedure. The equations for filter analysis are listed down below in the following equations:

Low pass filters:

$$h(k)=x(2k)+(g(k-1)+g(k)/8)$$

High pass filters:

$$g(k)=2.x(2k+1)-x(2k)-x(2k+2)$$

From the above equation, g (k) indicates the k^{th} high pass coefficient; h (k) indicates the k^{th} low pass coefficient; x (k) indicates the input pixel value at the k^{th} location. LL is the approximation coefficient, which encloses the most of the details of input image. LL part is chosen for the subsequent process of object segmentation in that Gray Level threshold value is chosen in LL part and Mathematical morphological operation are carried out for Skull removal.

3.3 Threshold segmentation using fuzzy set theory method

Let A be a given input image and M × M indicates the size that having L gray levels where '$\mu_A(a_{ij})$, $0 \le \mu_A(a_{ij}) \le 1$' is the membership value of '$(i,j)^{th}$' pixel in input image A. Exactly the fuzzy image can be denoted as 'A ={a_{ij}, $\mu_A(a_{ij})$}'. Let the count' (f)' mean the number of existences of the gray level 'f' in the given image [13]. The average gray level of the object region and the background region, respectively, are related to one another in the following way as a result of the unique threshold value t that was chosen to differentiate the item from the background:

$$\mu_0 = \frac{\sum_{f=0}^{t} f.count(f)}{\sum_{f=0}^{t} count(f)}$$

$$\mu_1 = \frac{\sum_{f=t+1}^{L-1} f.count(f)}{\sum_{f=t+1}^{L-1} count(f)}$$

The degree to which a pixel is drawn to the section of the image into which it can be placed determines the value that is assigned to its membership in that section. The employment of the Gamma distribution function was responsible for the establishment of the membership values of the image pixels. The below equation mentioned the common form of Gamma distribution,

$$f(x) = \frac{\left(\frac{(x-\mu)}{\beta}\right)^{\gamma-1} \exp\left(-\frac{(x-\mu)}{\beta}\right)}{\Gamma(\gamma)}, x \geq \mu, \gamma, \beta > 0$$

were, γ denotes shape parameter; μ denotes the location parameter; β denotes the scale parameter; finally, Γ denotes the Gamma function. If $\mu \neq 0$, $\beta = 1$ and $\gamma = 1$, the Gamma distribution in above equation takes the below form

$$f(x) = \exp[-(x-\mu)] \text{ as } \Gamma(1) = 1$$

The $\mu_A(a_{ij})$ (membership function) of the object region for given image can be calculated from above mentioned equation by choosing $\mu = \mu_1$ and the average gray level of object region is illustrated as,

$$\mu_A(a_{ij}) = \exp(-c.|a_{ij} - \mu_1|) \text{ if } a_{ij} > t,$$

In a same way, the $\mu_A(a_{ij})$ (membership function of the background region) can be calculated using above equation by selecting $\mu=\mu_0$, the average gray level of the background region. That is mentioned below

$$\mu_A(a_{ij}) = \exp(-c.|a_{ij} - \mu_0|)$$

$$\text{if } a_{ij} \le t,$$

Where, the constant 'c' has been used to confirm membership value of the gray level in the range [0, 1]. Here 'c' can been selected as 'c = $1/(f_{max} - f_{min})$', where 'f_{min}' and 'fm_{ax}' are the low and high gray level in the given image correspondingly. During the process of calculating the membership function, the full value of the distance between the mean of the object region to which a pixel belongs and the gray level of that pixel was measured. This

allowed for the accurate calculation of the membership function [14].

3.4 Mathematical morphology

In MR brain imaging application, skull stripping is a main point that indicates the non-cerebral tissues removing. To extract the MR image components such as region, description of shape, borders, and convex hull, the shape-based method known as mathematical morphology is used. Mathematical Morphology (MM) is a tool that was developed with set theory as its foundation. Examining the morphological structure of an input image is the primary goal of MM. This is accomplished by placing a small number of patterns, known as structuring elements, in various parts of the image (SE). Spectral elements, also known as SEs, are very small connected components of pixels that, when utilized in conjunction with other SE components, can be applied to the process of extracting significant morphological data from images. [15].

Erosion and dilation are two of the most important fundamental operations in MM, and they are also the operations that are utilized to derive other fundamental operations like opening and closure. Erosion and dilation are employed in the appropriate manner to scale down and scale up the individual components of an input image.

Let 'A' is a set (input binary image) and 'S' be the 'SE' in 'Z^2 '. AΘS denotes the Erosion of A by the S which is illustrated by below equation,

$$A\theta S = \{z|(S)_z \subseteq A\}$$

The term "Erosion of A by S" is used to refer to the collection of all pixels in which S is located at a pixel that is contained within "A," and the sign "AS" is used to represent this phenomenon. The erosion can be represented as a set of whole points in z. Erosion reduces the size of an object's shape, and it can be applied to images in order to remove inconsequential but aesthetically distracting details. Enlargement of A using S in Z^2 that is denoted by A⊕S. Enlargement of A using S and the group of all movements z, such that then A join by at least single component.

$$A \oplus S = \{z|(\hat{S})_z \subseteq A \neq\} \emptyset$$

The resulting image can be made taller and more substantial by using enlargement. In a similar manner, it is used to bring attention to the more subtle aspects of a medical imaging. The Opening and Closing operations are the most important ones in MM. The Opening operation makes the contours of an object smoother and then breaks the lines that are too narrow, and the Closing operation also smoothens the contours of the object, but it is primarily used to remove gaps and often removes small gaps between the objects. A○S denotes the opening operation and A●S denotes the closing operation, where A is the given input image and S is the SE. The calculation of erosion in the opening phase is done using dilation, and the calculation of dilation in the closing phase is done using erosion.

$$Opening, A^{\circ}S = (A\ominus S) \oplus S)$$

$$Closing, A \bullet S = (A \oplus S)\ominus S)$$

Morphological reconstruction is main operation in MM that is applied to extract some associated components which are marked in the given image. In order to build the morphological reconstruction, a series of dilation procedures are applied until the edge of the marker picture fits under a second image that is referred to as the mask image [15].

In MR brain image, automatic skull stripping is significant step in the neuro-image analysis. It is the process of removing non-cerebral tissues from an MRI of the brain, such as the skull and meninges, as well as the eyeball. This is done in order to better visualize the structure of the brain. A method for automatically stripping the cranium, which is dependent on the MM method, is proposed in this research study. The process behind the skull stripping method is discussed further down.

4. Result and Discussion

In this paper, the techniques applied for image segmentation are Threshold, Region growing and proposed (threshold based DWT using fuzzy set theory) segmentation algorithms. Comparative analysis is performed on each

segmentation method in an effort to achieve the highest level of precision and provide the best possible results. The proposed model has been validated on MATLAB 2018B, and it operates well on a computer equipped with an Intel i7 processor, a 2TB hard disk, 8GB RAM, and Windows 10 as the operating system.

4.1 Dataset Description

The datasets that were used in this research work were attained from the ADNI database, which was established in 2003 through the collaboration of the National Institute on Aging (NIA), the National Institute of Biomedical Imaging and Bioengineering (NIBIB), the Food and Drug Administration (FDA), private pharmaceutical companies, and non-profit organizations. The collection of data includes T1-weighted MR images in the sagittal plane, comprising 40 normal samples, 40 MCI samples, and 20 AD samples. There are 51 female samples and 49 male samples total. Their ages range anywhere from 57 to 95 years, with the average being 95.

4.2 Evaluation Parameters

The performance of different methods are mentioned in noise filtering section are compared with the various noise density range.

Table1. Performance Evulation using PSNR for Denoising the input image for different density range

S.NO		Hampel identifier	Adaptive median filter	Proposed
IM1	30%	20.24	21.75	**23.24**
	40%	17.25	21.03	**21.99**
	50%	21.24	20.97	**22.58**
IM2	30%	21.57	24.71	**25.72**
	40%	25.62	25.84	**26.37**
	50%	23.65	24.96	**26.08**
IM3	30%	24.52	28.51	**29.09**
	40%	23.69	29.61	**29.69**
	50%	24.81	27.15	**29.88**
IM4	30%	22.26	23.59	**25.31**
	40%	26.10	27.11	**27.60**
	50%	21.81	22.15	**25.88**
IM5	30%	25.00	26.46	**27.89**
	40%	23.69	27.69	**28.61**
	50%	28.25	29.13	**30.05**

Table 1 illustrates the PSNR results, which are achieved with the proposed method for p=30% to 50% of noise density levels. Still, if the noise density rises, the performance of existing filter not good. However the performance of Hampel Adaptive median noise filter is better than other existing filters with different kind of noise density range. Having segmentation performance evaluation procedures is a proficient way to examine the performance of existing algorithms and proposed algorithms. The segmented images are presented in fig 5

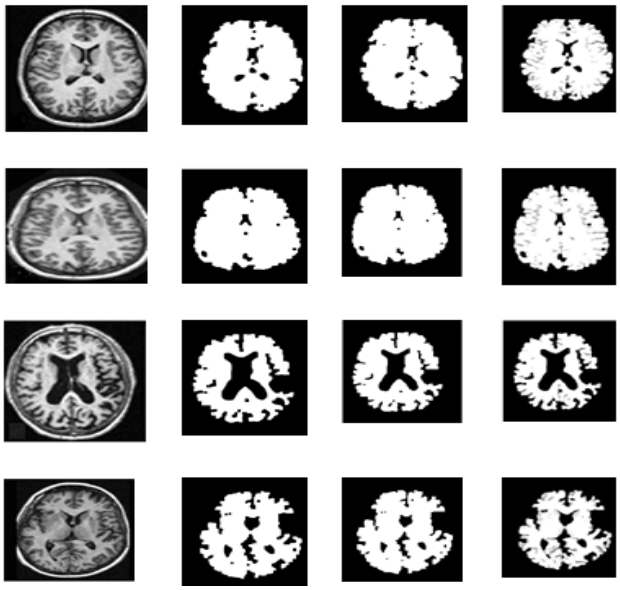

Figure.5. (a) Original Image (b) Otsu Threshold (c) Region Growing (d) Proposed

The Table 2 illustrates the existing and proposed algorithm performance by using PSNR evaluation metric,

Table.2Comparison of PSNR values for several segmentation algorithms

S.NO	OTSU Threshold (Decimal)	Region Growing (Decimal)	Proposed (Decimal)
IM1	47.32	50.59	54.68
IM2	50.02	52.69	55.86
IM3	51.05	53.59	57.35
IM4	49.23	53.26	56.00
IM5	50.13	52.61	54.00
IM6	48.70	51.79	55.52
IM7	47.03	50.21	54.52
IM8	49.68	52.76	55.03
IM9	48.04	52.80	56.28
IM10	47.16	51.07	53.19

Table 2 demonstrates very clearly that the suggested algorithm achieves the highest possible PSNR while segmenting AD MRI data. In order to evaluate how well the suggested technique performs on a variety of input images, it has been compared to various segmentation methods using the PSNR that was achieved from having the highest value from the proposed method. The comparative analysis is shown in following Fig 6.

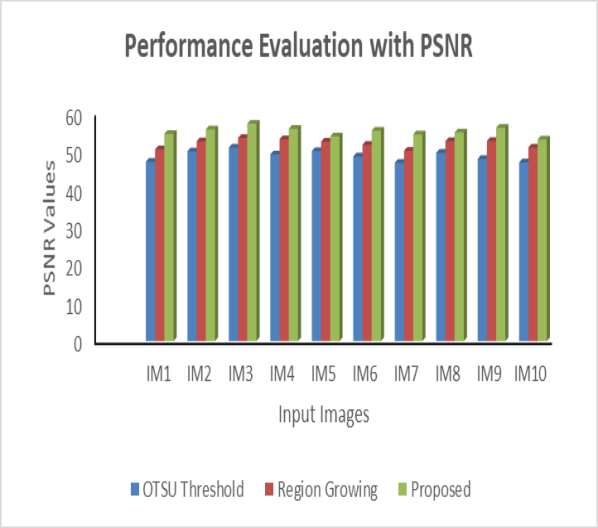

Figure.6. Comparative Analysis of the PSNR value for the Proposed Algorithm with the other existing segmentation algorithms.

Table.3. Comparing the mean squared error of several segmentation algorithms

S.NO	OTSU Threshold (Decimal)	Region Growing (Decimal)	Proposed (Decimal)
IM1	1.20	0.57	0.22
IM2	1.05	0.63	0.22
IM3	1.10	0.52	0.29
IM4	1.07	0.58	0.23
IM5	1.05	0.55	0.19
IM6	1.98	0.52	0.21
IM7	1.10	0.53	0.21
IM8	1.11	0.53	0.22
IM9	1.06	0.59	0.21
IM10	1.06	0.58	0.20

Table 3 demonstrates quite clearly that the proposed algorithm produces the least amount of MSE when it segments AD pictures. In order to have an idea of how well the suggested technique performs in relation to other segmentation algorithms and the different MRI pictures that are fed into it, the MSE that was produced from it was ranked lowest. The comparative analysis is shown Fig 7

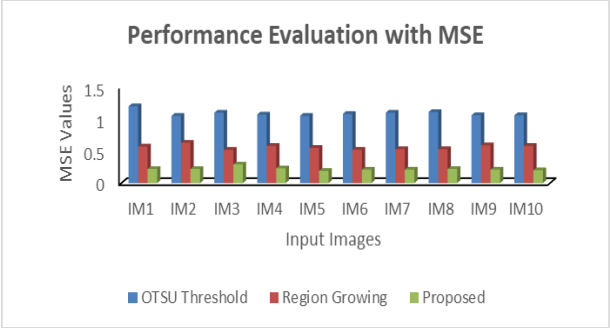

Figure.7.Comparative Analysis of the MSE value for the Proposed Algorithm with the other existing segmentation algorithms using ADNI datasets.

Table.4. Comparing the mean absolute error of several segmentation algorithms

S.NO	OTSU Threshold (Decimal)	Region Growing (Decimal)	Proposed (Decimal)
IM1	1.04	0.57	0.35
IM2	1.03	0.53	0.38
IM3	1.12	0.62	0.42
IM4	1.09	0.68	0.39
IM5	1.10	0.65	0.35
IM6	1.02	0.63	0.34
IM7	1.08	0.61	0.36
IM8	1.03	0.63	0.32
IM9	1.06	0.60	0.31
IM10	1.07	0.68	0.37

Table 4 demonstrates rather clearly that the proposed approach achieves the lowest possible MAE when segmenting AD images. In order to evaluate how well the suggested technique performs in relation to other segmentation algorithms and the various input images, the MAE that was derived from the proposed method was found to have the lowest value. The comparative analysis is shown in following figure

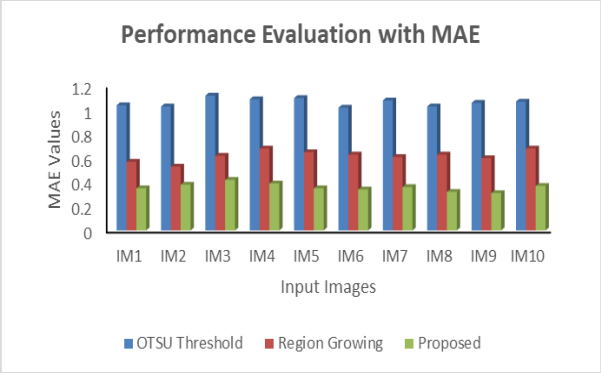

Figure.8. Comparative Analysis of the MAE value for the Proposed Algorithm with the other existing segmentation algorithms using AD-MRI datasets.

4.3 Performance Evaluation Metrics for image Segmentation Algorithms

Four performance metrics such as Peak Signal-to-noise ratio (PSNR), MSE (Mean Squared Error) and Mean absolute error (MAE) are utilized in this work to evaluate the performance of segmentation algorithms [16]. They are described below,

i. Peak Signal-to-noise ratio (PSNR):

The peak error is expressed as a decibel value, which is the unit of measurement used in the calculation. Before attempting to determine PSNR, one must first calculate MSE.

$$PSNR = 10 \log_{10} (R_2) / MSE$$

Extreme fluctuation, denoted by the letter R, in the image data format that was provided. R has a value of 1 for data types that are double precision and 255 for data types that are 8 bits unsigned.

ii. Mean Squared Error (MSE):

This measure is used to calculate the difference in quality between the original image and the segmented image, and it is derived using the equation that can be found below.

$$MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (g_{i,j} - f_{i,j})^2$$

The mean square error is calculated by taking the square of the Euclidean distance between the image that was input and the image that was produced. In above equation, $g_{i,j}$ is the input image and $f_{i,j}$ is the resultant image. i = *1, 2.., M* (range index) and *j = 1, 2.., N* (cross-range index).

iii. Mean absolute error (MAE):

The mean absolute error, or MAE, is a value that is calculated in order to evaluate how accurately projections correspond to the most recent results. The MAE is calculated using ,

$$MAE = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} \left(f_{i,j} - y_{i,j} \right)$$

In above equation, $f_{i,j}$ is the original image and $y_{i,j}$ is the evaluated image. i = *1, 2.., M* (range index) and *j = 1, 2.., N* (cross-range index).

5. Conclusion

This research proposes a brain image segmentation to detect the AD from the MRI using DWT based Fuzzy set theory Threshold method. A two-stage adaptive noise filtering system is devised in this research study. [Citation needed] In the first stage, an adaptive method is used to try to identify the noise that is there. After then, which filter, in conjunction with the Hampel filter, is used to denoise the input image? The method of segmentation is intended to be used for the purpose of segmenting the middle slice of the brain in an MRI by utilizing both proposed and morphological processes for skull stripping. T1-weighted MRI brain pictures from a dataset containing Alzheimer's disease were used to test the newly discovered approach. The effectiveness of the suggested procedure is validated by the visual perception of the skull after it has been stripped of the brain. The results of the suggested segmentation can be utilized, in their whole, for subsequent stages of image processing.

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