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Denoising of skull stripped brain tumor MR images

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Abstract— To improve the accuracy in segmenting the brain tumor from Magnetic resonance images (MR), pre-processing of raw MR images plays significant importance, is required for proper visualization and detection of the tumor part, to increase the quality of the image affected by the noise. The paper is mainly focused on skull removal and denoising techniques. Inclusion of skull may lead to misclassification of tumour tissues and might increase the time complexity. In this study T1, T1contrast, T2, Flair MR images is analysed in axial, sagittal and coronal planes. Mathematical morphology operation with histogram thresholding is performed to remove the skull region. Denoising the images with various filters and evaluation of filters in terms of mean square error (MSE), signal to noise ratio (SNR) and peak signal to noise ratio (PSNR) are considered for the study. The Algorithm developed provides better results for skull stripping and high PSNR is obtained for wiener filter reducing the Gaussian noise by preserving the edges.

Keywords— Denoising, MR Image, Morphology, , MSE, PSNR, Skull removal.

I. INTRODUCTION

Visualization and detection of brain tumor more precisely are still considered as the major research in bio-medical engineering. MR images has high significance compared to other imaging modalities in terms of high contrast soft tissues present describes the most internal features of the body that cannot be identified by CT, X-ray, PET etc., and is free from harmful radiation considered as non-invasive technique highly used in the application of identifying the brain tumour [1]. Gliomas are described as the tumor present in brain classified into four grades by WHO organization. Tumors can be either benign or malignant. Benign tumours comes under grade I which are in primary stage can be cured if ignored can become malignant (grade IV) [2]. Describing the stages of the tumor based on the features in algorithmic level is a challenging work. The image captured from MR machines usually comprised of three different views axial, coronal and sagittal with different sequences T1, T1contrast, T2, T2contrast and FLAIR. Detection of the tumor at the early stage describing the area of the tumor is of great interest. The MR images acquired will be in raw format suffering from the noise. Before performing segmentation process to detect the tumor, pre-processing techniques such as skull removal are required to enhance the quality of the image as it depends on the quality of the segmentation results [3]. Brain images consists of brain covered with skull, fluids, fats etc. skull must be stripped as it results in time complexity and reduces the misclassification. Skull stripping is difficult because of complex structure of brain [4]. Morphological operations like erosion, thresholding and masking are performed to remove the skull. MR images need to be denoised with different filters like median, non-local means, wiener, Gaussian, anisotropic diffusion are considered for denoising. Generally MR images suffer from salt and pepper noise. Median filter is used to remove more salt and pepper noise using a window size of 3x3 as it preserves the edges of the boundary makes more suitable for the analysis. Estimating parameters like MSE and PSNR are used to improve the performance of the filters. Segmenting the tumor part still remains an open problem as many researchers attempted various algorithms to figure out the region of interest. The computer aided image processing approaches can provide great help to radiologists as second opinion in analyzing the tumor area to come up with proper diagnosis or treatment as radiologists make the final decision [5]. Machine learning has become one of the wide research in biomedical field based on the patterns or features trained after obtaining results of segmented tumour. Pre-processing of MR images helps in providing the accuracy of automated segmented results makes it as one of the high priority step in image processing.

The overall paper is organized as, section I includes introduction, section II provides the literature survey carried out, section III explains the methodology work used, Section IV briefs results obtained and discussions, and section V contains conclusion and the future work to focus on.

II. Related Work

The presence of a skull in MR brain images consumes more time when processed. Stripping the skull from the image makes it suitable for providing accurate automated results of segmentation. F. Segonne et al. [6] proposed an efficient method removing the skull from MR brain images based on a hybrid technique of algorithms like watershed and deformable models. Watershed develops an initial approximation of the brain and surface deformation provides accurate skull stripped images. Andre G.R. Balan et al. [7] implemented a novel technique for stripping the skull from 3D MR brain images called Human Encephalon Automatic Delimiter (HEAD). It includes removal of the background and process of brain region extraction. The Gray level histogram is considered for the background removal, morphology and thresholding process are combined to extract the brain. Juan Eugenio Iglesias et al. [8] introduced a robust, learning based brain extraction system (ROBEST) for the skull stripping from MR brain images. It combined random forest classifier and point distribution model for stripping the skull. Random forest classifier detects the brain boundary and the point distribution model ensures the result seems to be reasonable. Lastly proved that ROBEST method produced more prominent result compared with other skull stripping methods. Francisco J. Galdames et al. [9] proposed efficient method for the skull stripping based on the concept of deformable models and histogram called as Simplex Mesh and Histogram Analysis Skull Stripping (SMHASS). The pre-processing method is applied for identifying the optimal start point for the deformation. Audrey H. Zhuang et al. implemented a mathematical modelling for the skull stripping based on model level set (MLS) [10]. The level set method evolves an active curve controlled by two terms, one developed from the mean curvature of the curve and other is designed to model the properties based on the intensity of the cortex in MR images. Orazio Gambino et al. proposed an automatic algorithm for stripping the skull using morphology and fuzzy c-means [11]. The morphological opening operator is used for differentiating the brain region from the non-brain part. Fuzzy c-means algorithm is identifies the background and the foreground of each transversal slice. Dwarikanath Mahapatra proposed a novel approach for the skull stripping of MR brain images using the information of prior shape [12]. The prior shape information is computed based on a set of labeled training images. Morphological operations are considered as the most common method used for skull stripping from MR brain images. Many methods for the separation of brain and non-brain tissues based on the concept of mathematical morphology are proposed [13-16]. It may not work properly in different sequences of MR images. An efficient method for the skull stripping based on the mathematical morphology, compatible with different MRI sequences such as T1, T2, FLAIR, and DWI is proposed. Saritha saladi et al. [17] analyzed denoising filters on MR brain images. Various filters for noise elimination in the images such as nonlocal means, principal component analysis, bilateral and spatially adaptive nonlocal means are studied (SANLM) are studied in which SANLM gives the better performance in terms of psnr and structure similarity. Iza Sazanita Isa et al. [19] evaluated denoising performances of basic filters on T2 weighted MR images. Three different algorithms such as median filter, Adaptive filter and average filter are considered, in which median filter outperforms other filters in removing Gaussian and salt and pepper noise. Thus, median filter gives better performance by preserving the edges. Ahmed faisal et al. [20] suggested improved denoising and segmentation technique for tumor detection from 2-D MR brain images. Fourth order partial differentiation is applied for noise removal. Compass operator helps to preserve the significant information at the edges and a new morphological approach for skull stripping leads to accurate tumor identification. R Balachander et al. [21] proposed efficient, robust denoising of MR brain images on wavelet based nonlocal means algorithm. Noisy image is decomposed into sub-band by wavelet transform and the nonlocal means filter is applied to each sub-band. This method preserves the coefficients obtained from wavelets and suppresses the noisy ones effectively. Perona and Malik [22] developed a multiscale smoothening of edges based on anisotropic diffusion filter in “Scale-space and detection of edges using anisotropic diffusion”. Anisotropic diffusion filter overcomes the drawback of filtering in the spatial domain and significantly improve the quality of the image by preserving object boundaries, removal of noise in homogeneous regions and edge sharpening and works on second order partial differentiation method. Jian yang et al. [23] developed pre-smooth, non-local means filter for denoising rician noise.

III. Methodology

In this section, the brain MR image datasets, and the methods used to perform skull stripping algorithm and various filters used for denoising the image is presented. The flow diagram of the pre-processing stages is given in Fig. 1. The detailed implementation of the steps is discussed in the following sections.

A. Brain Dataset

Dataset of 20 patients having glial brain images is considered for the study before undergoing any surgery. The data were acquired from the database in the department of radiodiagnosis, Mysore medical college and research institute and matrix imaging, division of Bangalore medical college. T1 weighted, T2 weighted, and FLAIR MR Sequences acquired on a 1.5 T Siemens MR machine with slice thickness 5mm and image pixel of 480x640.

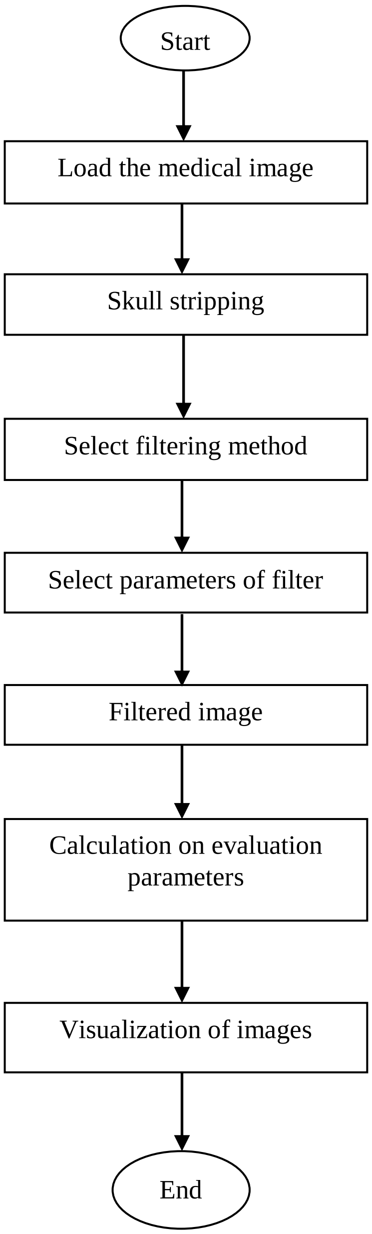


Fig. 1 Flow diagram

B. Skull stripping

Stripping the skull known as whole brain segmentation is a crucial step in removing the non-cerebral tissues like skull, fat, muscle and connective tissues. An algorithm is developed which combines both the concept of thresholding and morphological operations using multi sequence MR images. Stages of the skull stripping algorithm are given in Fig. 2.

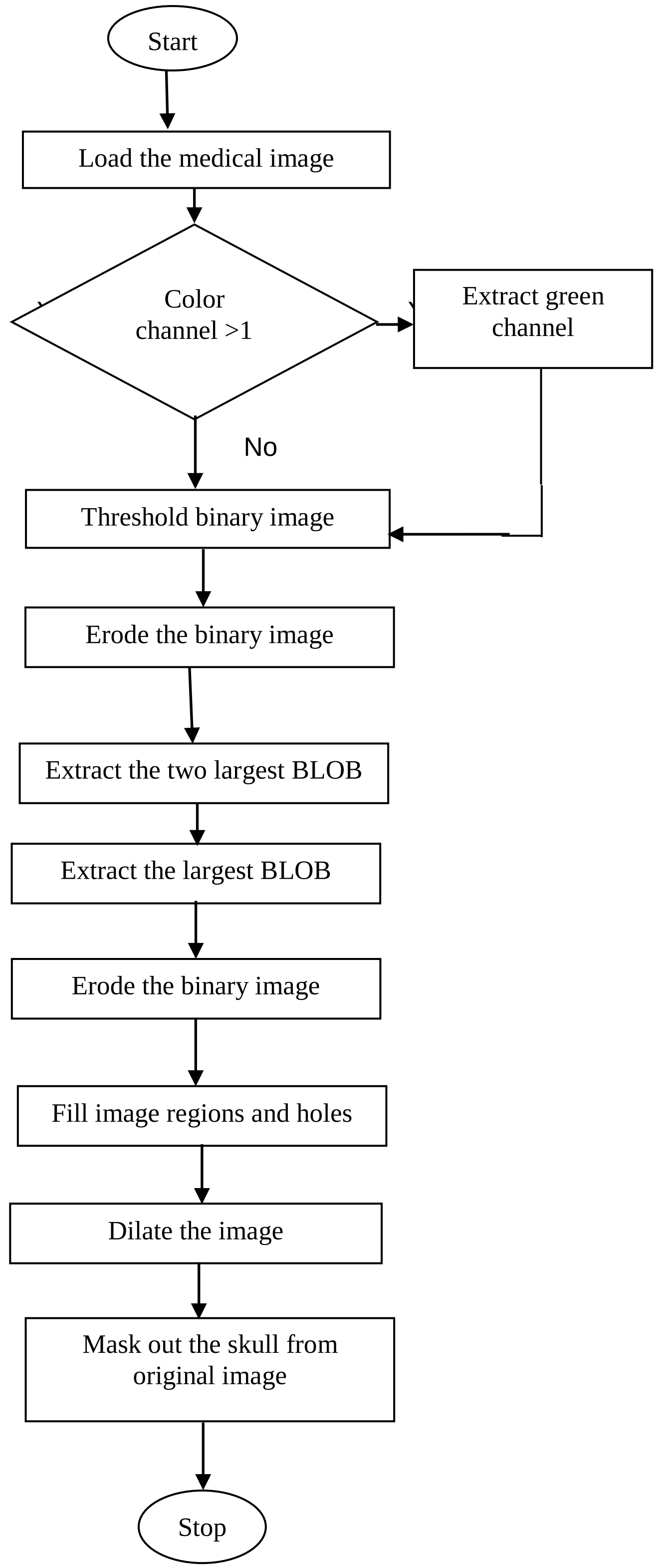


Fig. 2 Skull Stripping of the Brain

In fig.2, MR of the brain is loaded, converted to grayscale image extracting the green component, histogram is used for the selection of a threshold value, later two areas i.e., area of the brain and area of skull are considered if they are connected for the analysis. Erode operation is performed to extract the largest blob i.e., brain, fill any holes in the brain, dilation and the final binary image are masked with the original grayscale image to get a grayscale image with skull stripped away.

C. Denoising

Denoising is the process of removing the noise from the image, having a model for the process of degradation, it should be made possible for the inverse process applied to the image for restoring back to the original form. Denoising is highly required as a part of preprocessing in medical imaging, to obtain better quality of medical images and more precisely to diagnose the disease. Various filtering techniques like median filter, adaptive filter (wiener), gaussian filter, average filter, anisotropic diffusion filter and non-local means filter is considered in the analysis of removing noise from the MR image and is compared with the parameters like PSNR, MSE and SNR.

i) Median Filter

Median filter is a nonlinear method used for removing the noise from MR brain images and is very effective in removing salt and pepper noise. The median filter is performed in pixel by pixel fashion by replacing each value of the pixel with the median value of neighbouring pixels. The entire pixel values are sorted out and replace the pixel by the median of the gray levels in the neighbourhood of that pixel. The median filter removes the noise without reducing the sharpness of the image, thus mainly used in medical imaging applications.

$$f(x,y) = \text{median}\ \{g(s,t)\}\ \text{Where}\ (s,t) \in S_{xy} \qquad (1)$$

ii) Gaussian filter

Improvement of filtration is achieved by the mask of the filter with the function describing the Gaussian distribution. Gaussian distribution is approximated to the binominal distribution, thus the filter becomes suitable for filtering in the spatial domain. Gaussian filter takes less time to execute. The two dimensional Gaussian function is used to work with images, i.e., the product of two 1Dimensional Gaussian functions (one for each direction) and is usually given by,

$$G(x,y) = \frac{1}{2\pi\sigma^2}\ e^{-(x^2+y^2)/2\sigma^2} \qquad (2)$$

Where σ= standard deviation

x&y=distance from the origin in horizontal & vertical axis

iii) Wiener Filter

Wiener filter is the optimized technique of inverse filters and noise smoothening, which removes additive noise and smoothens simultaneously. Wiener filters called as adaptive is an optimum linear filter containing the noisy data as input, which involves the calculation of the difference between the desired output sequences from the actual output. The adaptive filter compared with the other linear filter provides more smoothening by preserving the edges and other high frequency regions in an image.

iv) Mean Filter

Mean filter is a linear filter where the mask is applied to each pixel in the image. The pixels under the same mask are averaged forming a single pixel called as average filter. Let S_{xy} be the coordinates in a rectangular sub image window of size m × n centered at point (x,y). The mean filter computes the average value of the affected image g(x,y) in the area defined by S_{xy}. The value of the restored image f at any point (x,y) is the mean computed between the pixels in the region defined by S_{xy} is given by,

$$f(x,y)=\frac{1}{mn}\sum_{(s,t)\in Sx,y} g(s,t) \qquad (3)$$

v) Anisotropic diffusion Filter

The basic equation of anisotropic diffusion equation given by

$$\frac{\partial I(x,y,t)}{\partial t} = \text{div}[g(\|\nabla I(x,y,t)\|)\nabla I(x,y,t)] \qquad (4)$$

Where t is the time parameter, is the original image, is the gradient of the image at time t, this function is chosen to satisfy $\lim_{x\to 0} g(x)=1$, so that the diffusion is maximal within uniform regions, and $\lim_{x\to\infty} g(x)=0$, so that the diffusion is stopped across edges. Two such functions proposed by Perona and Malik were

$$g_1(x) = \exp\left[\left(\frac{-x}{k}\right)^2\right] \qquad (5)$$

$$g_2(x) = \frac{1}{1+(\frac{x}{k})^2} \qquad (6)$$

Where K is the gradient magnitude threshold parameter controlling the rate of the diffusion and produces soft threshold between the image gradients attributed to noise and edges.

Perona and Malik discretized their anisotropic diffusion equation to,

$$I_{t+1}(S) = I_t(S) + \frac{\lambda}{|\eta s|}\sum_{P\in\eta s} g_k(|\nabla I_{s,p}|)\nabla I_{s,p} \qquad (7)$$

Where I is a discrete sampled image, s denotes the position of the pixel in the discrete 2-D grid, t denotes the iteration step, g is the conductance function and K is the gradient threshold parameter. Constant $\lambda \in (0,1)$ determines the rate of diffusion and where $\boldsymbol{\eta}_s$ ={N, S, E and W} where N, S, E and W are the North, South, East and West neighbours of pixel s, respectively. Consequently, is equal to 4 (except for the image borders). The symbol which in the continuous form is used for the gradient operator represents a scalar defined as the difference between neighbouring pixels in each direction

$$\nabla I_{s,p} = I_t(P) - I_t(S), \quad P \in \boldsymbol{\eta}_s = \{N,S,E,W\} \tag{8}$$

vi) Non-Local Means filter
The conventional NLM algorithm denoises the image based on the fixed size search window for each pixel. Let $y(i)$ and $x(i)$ is the observed noisy and original image pixels respectively, where i is the pixel index. Assumption is made that the original image is corrupted by independent and identically distributed Gaussian noise $(0,\sigma^2)$with zero mean and variance σ_n^2 such that,

$$Y(t)=x(t)+ \boldsymbol{\eta}(i) \tag{9}$$

The estimated pixel values is calculated based on the weighted average of all grey values within the entire image as

$$x_{NLM}(i) = \frac{\sum_{j\in s} w(i,j)y(j)}{\sum_{j\in s} w(i,j)} \tag{10}$$

Where $x_{NLM}(i)$ is the restored pixel value at pixel i. The weights $w\ (i, j)$ indicates the amount of similarity between the neighbourhoods centered at pixel i and at pixel j in predefined search region S.

$$W\ (i,j) = e^{\frac{\|N(i)-N(j)\|^2}{h^2}} \tag{11}$$

Where h is the smoothening parameter controlling the extent of averaging. The small value of h leads to the noisy results almost identical to input, while a very large h results in an overly-smoothed image. $N\ (i)$ and N (j) define the $P\times P$ square neighbourhoods. S_i is a square search window of size $S \times S$ centered on pixel i. The vector norm used in the above equation is the Gaussian weighted Euclidean distance with standard deviation σ.

IV. Results and Discussion

A skull stripping algorithm is developed for multi sequence MR brain images in all the 3 planes. As the MR brain images suffer from Gaussian noise, six denoising filters are used to remove noise based on the parameters. The performance evaluation metrics are discussed as follows,

A) Mean square error (MSE)
MSE is computed by averaging the squared intensity differences of distorted and reference image pixels.

$$MSE = \frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}[I(i,j) - k(i,j)]^2 \tag{12}$$

Where M=rows and N=columns
I=original raw noisy image and K=noise free image

B) Peak Signal to Noise Ratio (PSNR)

PSNR is the ratio between maximum possible power of a signal and the power of corrupting noise. Higher the PSNR better the quality of the image.

$$PSNR = 20\log_{10}Max_i - 10\log_{10}MSE \tag{13}$$

Where Max is uint8 image i.e., 255
MSE=mean square error

C) Signal to Noise Ratio (SNR)

SNR is used in imaging as a physical measure of the sensitivity of an imaging system.

$$SNR= 10\log_{10}\left(\frac{var(x)}{var'(x)-var(x)}\right) \tag{14}$$

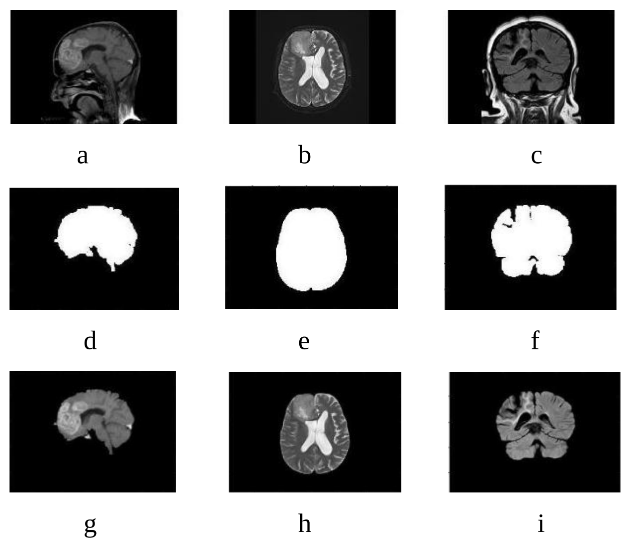
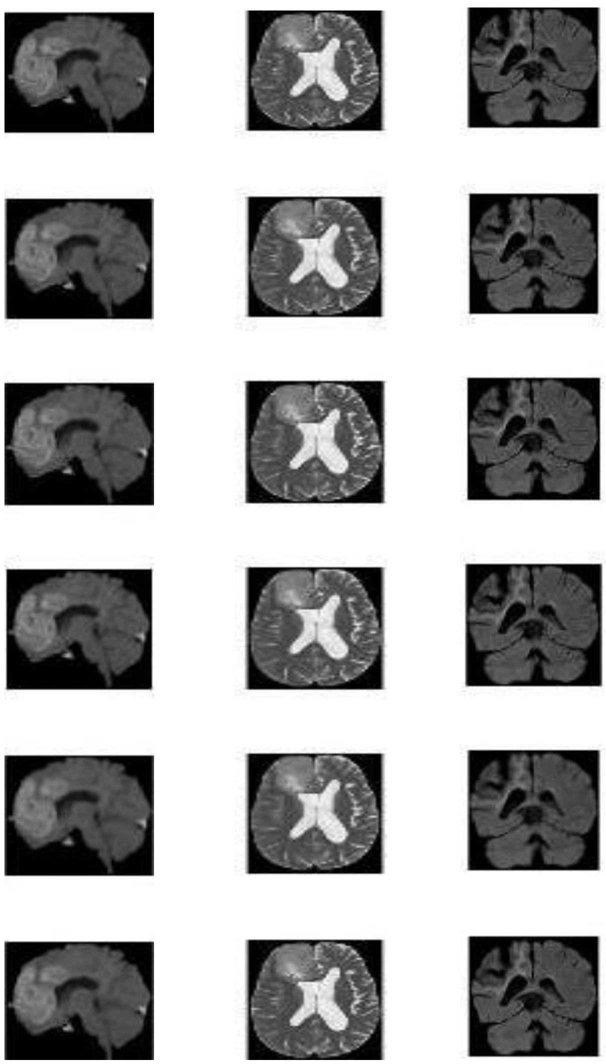


Fig.3 a) T1 sagital view, b) T2 axial view, c) FLAIR coronal view. d-f are binary mask, g-i are final skull stripped images.

Comparison of various filters is computed and shown in table 1. In first stage skull stripping is performed on the MR images based on histogram thresholding and mathematical morphological operations. In fig 3, a-c represents the original MR images with skull, d-e represents the binary threshold based on the histogram of respective images, g-i represents the final gray image with skull free is obtained after masking the dilated image with the original MR image. In second stage denoising is processed from the output of skull stripped images with different filters and the results are shown in fig 4. Wiener filter provides least MSE, better PSNR and SNR as shown in table 1, table 2 and table 3 respectively. In the fig 4 (last row), the non-local means filter provides the better smoothing. In this study skull stripping provides better results in all the 3 planes as many researchers rely only on axial plane for the detection of tumor.



a b c

Fig.4 a) Filtered results of median, gaussian, wiener, mean, anisotropic, NLM for T1 sagital view, b) Filtered results of median, gaussian, wiener, mean, anisotropic, NLM for T2 axial view, c) Filtered results of median, gaussian, wiener, mean, anisotropic, NLM for FLAIR coronal view.

Table 1. Evaluation of MSE of various filters

Sl No	Median	Gaussian	**Wiener**	Mean	Anisotropic	NLM
Image1	0.44	1.18	**0.08**	1.21	2.6	1180
Image2	1.85	4.2	**0.56**	4.33	9.76	3540
Image3	0.33	0.83	**0.18**	0.85	5.43	1055
Image4	0.61	1.26	**0.21**	1.3	5.79	1155
Image5	0.66	1.3	**0.22**	1.34	5.63	888
Image6	0.17	0.34	**0.05**	0.35	2.34	335

Table 2. Evaluation of PSNR (in db) of various filters

Sl No	Median	Gaussian	**Wiener**	Mean	Anisotropic	NLM
Image1	51.68	47.4	**58.84**	47.32	43.99	43.05
Image2	45.45	41.9	**50.63**	41.76	38.24	40.08
Image3	52.94	48.93	**55.66**	48.81	40.78	41.88
Image4	50.3	47.13	**54.89**	46.99	40.51	41.66
Image5	49.93	47.0	**54.63**	46.86	40.63	41.75
Image6	55.93	52.76	**61.15**	52.66	44.44	43.69

Table 3. Evaluation of SNR (in db) of various filters

Sl No	Median	Gaussian	**Wiener**	Mean	Anisotropic	NLM
Image1	34.2	30.0	**41.4**	29.9	26.5	25.6
Image2	32.8	29.2	**38.0**	29.1	25.5	27.4
Image3	35.0	31.0	**37.7**	30.9	22.8	23.9
Image4	32.8	29.6	**37.4**	29.4	22.9	24.1
Image5	31.3	28.3	**36.0**	28.2	21.8	23.1
Image6	33.0	29.8	**38.3**	29.7	21.4	20.8

V. CONCLUSION AND FUTURE SCOPE

A skull stripping algorithm is developed based on histogram thresholding and morphological operations and denoising of MR images is performed on multi sequence images such as T1, T2 and FLAIR in different planes like axial, sagital and coronal planes. In this study 20 patients with brain tumor (low grade glioma and high grade glioma) are considered. Skull stripping has obtained better results in all planes of MR image as shown in fig3. The comparison with different filters in table 1, table 2 and table 3 shows that wiener filter provides better result in removing gaussian noise by preserving the edges. Non local means filter provides better smoothening compared to others. Less MSE and high PSNR values in decibel indicates the high quality of the image. Preprocessing stage is highly required for accurate analysis of the segmentation in detecting the brain tumor at the earliest stage.

Future work will be focused on segmenting the tumor from the brain accurately defining the proper shape, size and stage of the tumour based on the features extracted.

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