Computer Aided Detection of Brain Tumor in Magnetic Resonance Images

Abhishek Raj, Alankrita, Akansha Srivastava, and Vikrant Bhateja

***Abstract*— Brain tumor is an abnormal mass of tissue with uncoordinated growth inside the skull which may invade and damage nerves and other healthy tissues. Non-homogeneities of the brain tissues result in inaccurate detection of tumor boundaries with the existing methods for contrast enhancement and segmentation of magnetic resonance images (MRI).This paper presents an improved framework for computer aided detection of brain tumor. This involves enhancement of cerebral MRI features by incorporating enhancement approaches of both the frequency and spatial domain. The proposed method requires de-noising in wavelet domain followed by enhancement using a non-linear enhancement function. Further an iterative enhancement algorithm is applied for enhancing the edges using the morphological filter. Segmentation of the brain tumor is finally obtained by employing large sized structuring elements along with thresholding. Simulation results along with the estimates of quality metrics portray significant improvement of contrast, enhancement of edges along with detection of boundaries in comparison to other recently developed methods.**

***Index Terms*— brain tumor, daubechies wavelet, discrete wavelet transform, sigmoid function, magnetic resonance imaging, morphological filter, structuring element.**

I. Introduction

Human beings have battled cancer since their existence, of which every year more than 200,000 people in US are diagnosed with a primary or metastatic brain tumor. Automated detection and segmentation of brain abnormalities is therefore a challenging problem of research since decades. Solid brain tumors are malignant masses of tissues formed inside skull as a result of abnormal and uncoordinated growth due to proliferation of atypical cells. The grown mass may evolve in a more complex manner, once it starts affecting the neighboring healthy tissues and nerves. Neuro-radiologists classify brain tumors into two groups, namely: glial tumors (gliomas) and non-glial tumors [1]. MR images are noisy and suffer from poor contrast. Due to these miscellanea in tumor characteristics for different patients, coupled with the limitations posed by the various image acquisition devices, analysis of MR images, becomes a complex task, even for the skilled neurologists. The comprehensive survey indicates the exponential increase in the magnitude of research going on in the medical world for brain cancer indicating the fatal traits of brain tumor. An efficient image contrast enhancement module followed by edge enhancement and segmentation is the primary requirement of any computer aided detection system employed for medical diagnosis. In this paper, a new method for computer aided detection of brain tumor is proposed which consists of contrast improvement of cerebral MRI features followed by segmentation of targeted region of interest (ROI). The proposed framework will aid in the accurate diagnosis of tumor patients. This paper is structured as follows: section I gives a brief introduction of brain tumor. Existing image enhancement techniques have been discussed in the section-III, while an overview of wavelet transform has been given in the third section. Section-IV explains the proposed method. The objective evaluation parameters have been described in the fifth section and the experimental results discussed under section-VI. Seventh section draws the conclusion, whereas the scope for future improvement is given under section VIII.

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Abhishek Raj, Alankrita, and Akansha Srivastava are B.Tech. final semester students in Department of Electronics and Communication Engineering, Shri Ramswaroop Memorial Group of Professional Colleges, Lucknow (U.P.), India (e-mail:abhishekraj1989@gmail.com, iamalankrita@gmail.com, akanshas2412@gmail.com).

Vikrant Bhateja is Assistant Professor in Department of Electronics and Communication Engineering, Shri Ramswaroop Memorial Group of Professional Colleges, Lucknow (U.P.), India (e-mail: bhateja.vikrant@gmail.com).

II. Literature Review

To facilitate computer aided detection of brain tumor, it is known that the image information (from existing modalities: MRI, CT scan, etc.) alone is insufficient to differentiate between the normal and abnormal tissues as well as the background. Brain lesions show poor contrast with respect to the background, presenting highly inhomogeneous patterns. Common methods for image contrast enhancement include techniques such as histogram equalization [2], mathematical morphology [3], and transform domain techniques such curvelet transform [4]. There are two possible approaches to enhance image features: first one is the removal of background noise; the other is to increase the contrast of suspicious areas by linear or nonlinear operations. However, these conventional enhancement techniques pose limitations such as inappropriate enhancement of the ROI, thereby complicating the process of image segmentation. The present work proposes a combination of these traditional contrast enhancement algorithms coupled with some modifications to enhance the targeted lesion with respect to its background without enhancement of noise and other artifacts. Wavelet analysis serves as an important tool for the practical implementation of image denoising and enhancement in the frequency domain. Significant amount of design flexibility can be obtained using wavelet transform. Choice of requisite level of decomposition, selection of wavelet family, spatial frequency tiling coupled with various thresholding techniques can be well optimized for enhancement as well as background noise suppression in the region of interest. Kim *et al.* used partially overlapped sub-block histogram equalization (POSHE) technique [2] for image enhancement. The technique used a blocking effect reduction filter (BERF) for suppression of the blurring effect. But, this in turn leads to a trade-off problem between visual quality and computational speed-up. Kharrat *et al.* proposed a morphological filter [3] for contrast enhancement of magnetic resonance images using structuring element of radius 30 pixels followed by segmentation. However, usage of large sized structuring elements poses the problem of image blurring leading to loss of useful information. Also, the hardware implementation of large sized structuring element is cumbersome. Starck *et al.* proposed an algorithm [4] for enhancement of gray and color images using curvelet transform. This transform based approach works better than the wavelet transform in case of noisy images, however for near noiseless images this transform is not well suited. The edges and contours can be detected effectively using wavelets in such cases. Yang *et al.* proposed an algorithm [5] for medical image denoising by soft thresholding using wavelet transform followed by enhancement using non linear histogram equalization. Besides enhancing the ROI, histogram equalization also enhances the noise contents of the image which is undesirable. Sardy *et al.* proposed a robust wavelet based estimator for image de-noising [6]. However, the authors have used a universal threshold parameter for image denoising. Universal threshold computes a global threshold value for the image without emphasizing on local details. As a consequence, undesired blurring is observed. Chen *et al.* proposed image denoising using neighborhood wavelet coefficients [7]. This approach is based on the assumption that adjacent wavelet coefficients have similar value. Hence, this algorithm will not produce optimal results for images with sharp edges and variations. Arulmozhi *et al.* proposed three spatial domain filters [8] for contrast enhancement. These algorithms were application specific, but the author has not mentioned in particular that, which technique works best for which specific application. In addition to this, the author suggests to apply histogram equalization on the final enhanced output, which could lead to over enhancement. Contrast limited adaptive histogram equalization (CLAHE) [9] can provide subtle edge information but might degrade performance in the screening setting by enhancing the visibility of nuisance information. This paper presents an improved framework for computer aided detection of brain tumor by incorporating multiscale analysis, thereby assisting neurologists in early detection of cerebral cancer. The proposed method requires denoising and enhancement using a non-linear enhancement function in wavelet domain followed by the application of an iterative enhancement algorithm using the morphological filter to further enhance the edges and filter out the residual noise. The proposed morphological filter uses a variable sized structuring elements (not exceeding, a symmetric size of 5×5), thereby providing a consistent enhancement of ROI along with suppression of background noise. Segmentation of the brain tumor is finally obtained by employing large sized structuring elements along with thresholding.

III. Wavelet Transform and Multi-Scale Analysis

The primary aim of wavelet analysis is to decompose a given input signal on a set of 'basis functions'. To capture the frequency evolution of a non-static signal, it is necessary that the basis function should have a compact support in both time and frequency domain [10]. A continuous wavelet transform decomposes an input signal over dilated and translated wavelet function. The wavelet transform of a signal at time u and scale s is performed as

$$Wf(u,s) = \langle f, \Psi_{u,s} \rangle = \int_{-\infty}^{+\infty} f(t) \frac{1}{\sqrt{s}} \Psi^{*}(\frac{t-u}{s}) dt = 0 \tag{1}$$

Assuming that the energy of $\Psi^{*}(\omega)$ is concentrated in a positive frequency interval centered at η, the time-frequency support of a wavelet atom $\Psi_{u,s}(t)$ is symbolically represented by a Heisenberg rectangle centered at $(u, \eta/s)$ with time and frequency supports spread proportional to s and $1/s$ respectively. An orthogonal (non-redundant wavelet transform) can be constructed by dicretising the dilation parameters on an exponential sampling using fixed dilation steps, on the other hand, the translation parameter can be varied in integral multiples of a dilation dependent step [11]. For the purpose of medical imaging one has to generally deal with the discrete pixel intensities. Therefore, the focus centers on discrete wavelet transform. Wavelets find extensive applications in image processing. Since an image is two dimensional, so the dimensionality of wavelet transform for images is also increased by one. Hence, wavelet transform for an image is given by:

$$W_t\left(p;q_1 q_2\right) = f\left(y_1, y_2\right), \varphi_{a;q_1,q_2}\left(y_1, y_2\right)$$
$$= \frac{1}{p} \iint f\left(y_1, y_2\right) \varphi\left(\frac{y_1-q_1}{p}, \frac{y_2-q_2}{p}\right) dy_1 dy_2 \quad . \tag{2}$$

where: translation in two dimensions is given by q_1 and q_2. Similarly, the inverse wavelet transform can be computed as:

$$f\left(y_1, y_2\right) = \frac{1}{r_\varphi} \int_0^\infty \frac{dp}{p^3} \iint W_t\left(p; q_1, q_2\right) \varphi\left(\frac{y_1-q_1}{p}, \frac{y_2-q_2}{p}\right) dq_1 dq_2 \quad . \tag{3}$$

where:

$$r_\varphi = \frac{1}{4\pi^2} \iint \frac{|\varphi(\omega_1, \omega_2)|^2}{\left|\omega_1^2 + \omega_2^2\right|} d\omega_1 d\omega_2 \quad , \tag{4}$$

$$\varphi_{a;q_1,q_2}(y_1, y_2) = \frac{1}{p} \varphi(\frac{y_1-q_1}{p}, \frac{y_2-q_2}{p}) \quad . \tag{5}$$

and $\varphi_{a;q1,q2}(y_1,y_2)$ is basic wavelet function in two dimension [12].

IV. Proposed Computer Aided Detection Framework

This paper proposes an improved framework for computer aided detection of brain tumor in MR images. This involves enhancing the contrast of cerebral MRI features by incorporating enhancement approaches of both the frequency and spatial domain as shown in the block diagram in Fig. 1. Multiscale analysis techniques are employed, which decomposes an image signal using wavelets followed by enhancement and de-noising of only those sub images which contain the necessary information. This has been detailed in wavelet analysis module shown in Fig. 2. Morphological filter is then applied to the reconstructed image to further enhance the features along with filtering of residual noise. The block diagram of the morphological edge enhancement of cerebral MRI features is shown in Fig. 3; and Fig. 4 gives the flow diagram for the segmentation module. The working of each of these modules (Fig. 2 to Fig. 4) is detailed in the following subsections.

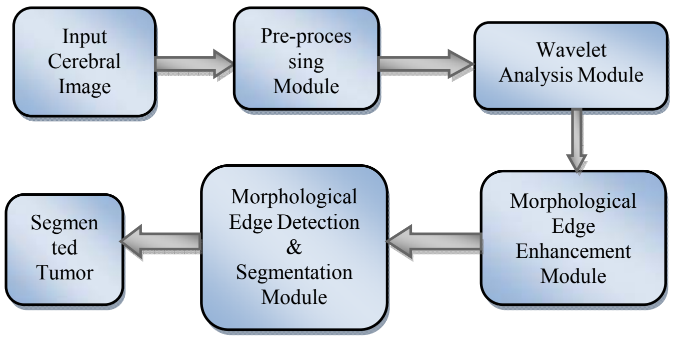


Fig. 1. Proposed framework for computer aided detection of brain tumor in MR images.

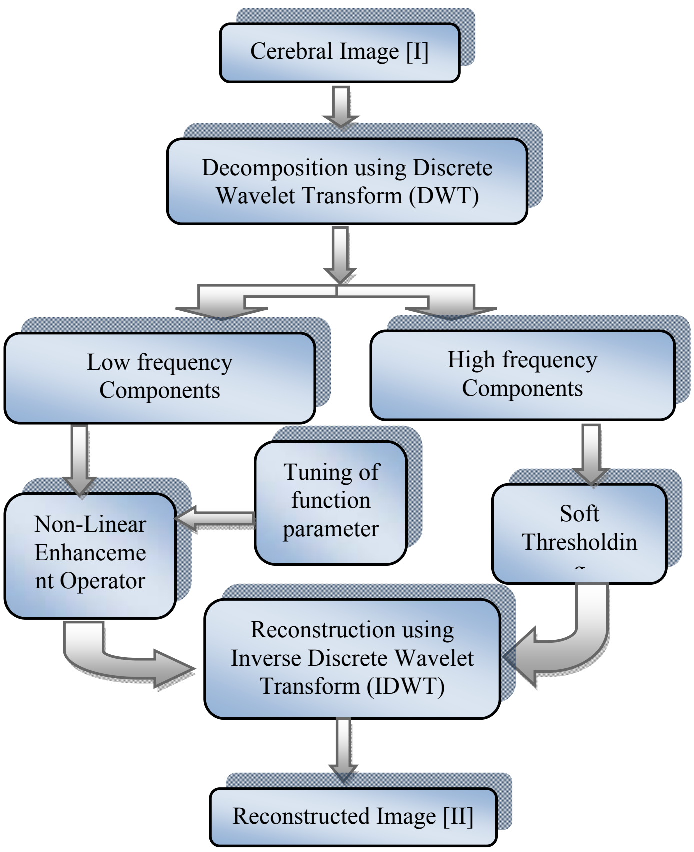


Fig. 2. Wavelet Analysis module

A. Wavelet Based Sub-band Coding

In wavelet transform, an image is represented at different resolution levels. It decomposes any image into low frequency approximation coefficients and high frequency detail coefficients, viz. horizontal, vertical and diagonal coefficients, at any resolution. Discrete Wavelet Transform (DWT) transforms the image into an array of wavelet coefficients. These coefficients are then modified as per the requirement and the image is reconstructed from these modified coefficients by using Inverse Discrete Wavelet Transform (IDWT). In the proposed method, a two-level decomposition of the input signal is performed using daubechies wavelet family. In the higher frequency spectrum, with the increase in the information content, noise also increases. Therefore, de-noising is performed by doing soft thresholding of the high frequency coefficients.

Soft Thresholding [5] can be mathematically defined as:

$$f(t)=\begin{cases} t-T_h; t\geq T_h \\ t+T_h; t\leq -T_h \\ 0; |t|<T_h \end{cases} \quad (6)$$

As in different high frequency sub-images, the noise properties are different, different threshold levels are used for each sub-image. The threshold T_h is defined as:

$$T_h=\sigma\sqrt{2\log N_i} \quad (7)$$

where: σ is the noise standard deviation and N_i is the size of sub-image. After accessing the coefficients at the fine level, IDWT is applied for reconstructing the image back into the spatial domain. The non-linear enhancement operator is then applied to the approximation coefficients. This module has been shown in Fig. 2.

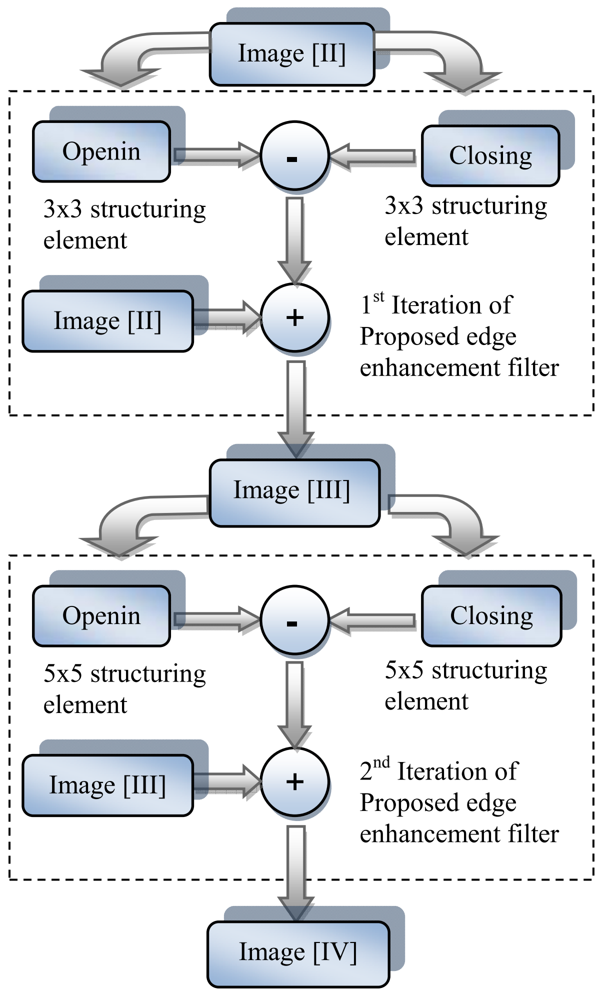


Fig. 3. Morphological Edge Enhancement module

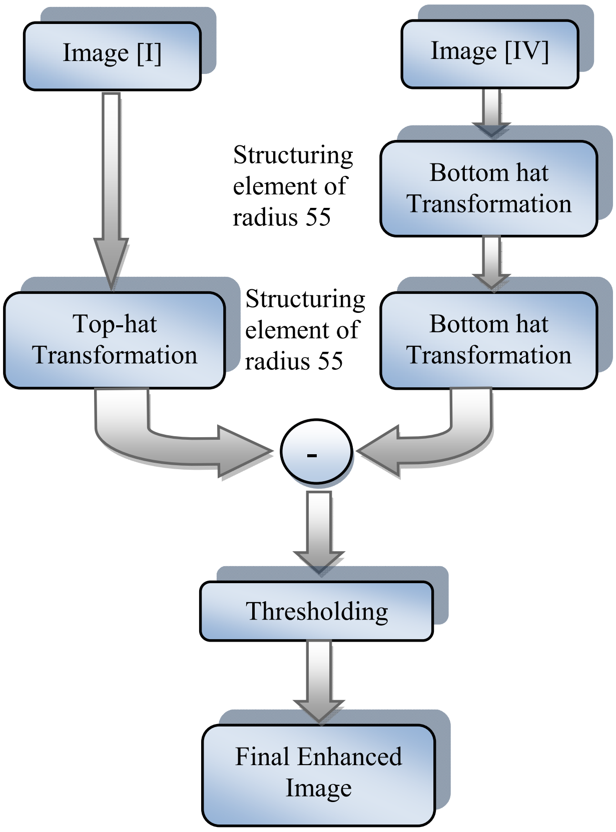


Fig. 4. Morphological Segmentation module

B. *Non Linear Enhancement Operator*

The fundamental problem posed in the enhancement of brain tumor images is the inability to emphasize the desired features without the enhancement of noise. This drawback is overcome by the global enhancement techniques equipped with multistate Adaptive Gain [13]. A logistic function is real-valued, differentiable, and monotonically increasing function given by:

$$logistic(x) = \frac{1}{1+e^{-x}} \quad (8)$$

This is also the requirement of the non-linear transformation function for conventional histogram equalization. The graphical variation for *logistic(x)* is shown in Fig. 5(a). Linear combination of logistic functions with an adaptive gain factor is used for the preparation of non-linear mask for contrast enhancement of cerebral MRI features. This mask is spatially moved over the ROI to produce the enhanced image. The function modifies the gray levels by suppression of pixel values of very small amplitude, and enhancement of only those pixels larger than a certain threshold within each level of the transform space. The non-linear enhancement operator [14] (as shown in Fig. 5(b)) used to accomplish the above operation is given by:

$$y(x) = a[logistic\{k(x-b)\} - logistic\{-k(x+b)\}] \quad (9)$$

where: x denotes the gray level value of the original ROI at co-ordinate (i, j). k and b are the parameters for control of enhancement and the threshold respectively and a is given by:

$$a = \frac{1}{logistic\{k(1-b)\} - logistic\{-k(1+b)\}} \quad (10)$$

where: the parameters $b \in R$ while $k \in N$.

The enhancement operator *y(x)* is differentiable as well as continuous, hence it is monotonically increasing within the interval [-1, 1]. This further ensures that the enhancement using *y(x)* does not include any discontinuities into the enhanced image. In this approach, the threshold parameter *b* controls the noise level of the ROI during the process of enhancement. All the pixel intensity values above the threshold level are enhanced while the ones below it are suppressed. This threshold level can be calculated by solving the equation *y(x)-x*=0 or by finding the standard deviation of pixel values.

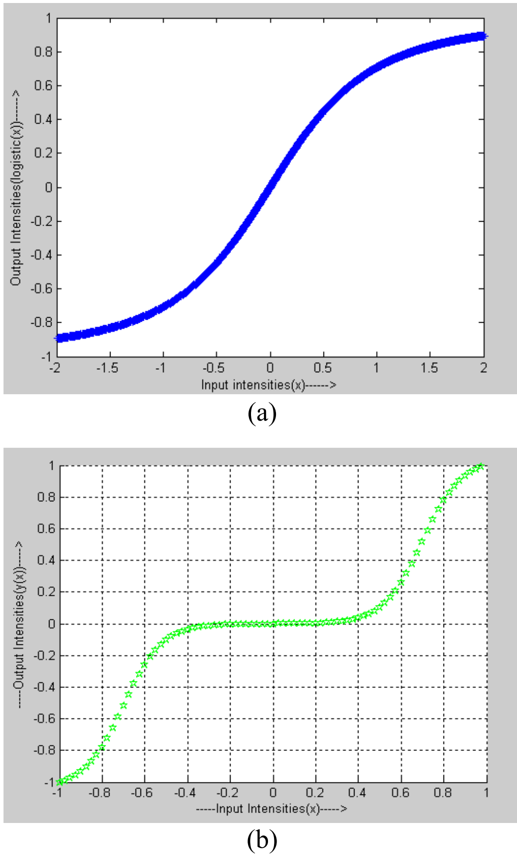


Fig. 5 **(a)** Graphical variation of Logistic Function [*logistic(x)*], **(b)** Graphical variation of Non-Linear Enhancement operator *y(x).*

However, with the above function (9), the threshold is controlled through the parameter b (where $0<b<1$, $b \in R$) while, the effective contrast enhancement can be controlled through the parameter *k*.

C. *Morphological Filter*

Morphological filters are non-linear filters commonly used as a tool for noise filtering, contrast enhancement as well as edge detection. This is achieved by the application of basic morphological operations using a structuring element. Flat and symmetric structuring elements of larger size are primarily used for noise removal, while contrast enhancement of small sized objects can be achieved by using small sized structuring elements, although it might be comparatively difficult to suppress noise. Image features similar in shape to that of the structuring element remains unaltered, while others are either extracted or suppressed. So the choice of structuring element depends on the type of information to be retrieved [15]. Erosion, dilation, opening and closing are among the common morphological operations. Dilations and erosions can be combined in a variety of ways to solve wide range of problems involving non linear filtering [16]. As the names suggests, erosion shrinks an image while dilation expands it. In erosion, when the structuring element passes over an image then the intensity of the neighborhood pixel with minimum value is considered. This reduces the brightness and hence the size of the image. On the contrary, dilation selects the pixel with maximum intensity value thereby increasing its brightness and size. Another set of morphological operations used are opening and closing. Opening is defined as erosion followed by dilation. Small islands and thin filaments of object pixels are removed by this operation. Mathematically, opening is expressed as:

$$A \circ B = (A \Theta B) \oplus B \quad (11)$$

Likewise, islands and thin filaments of background pixels are removed by closing. It is dilation followed by erosion [17].

$$A \bullet B = (A \oplus B) \Theta B \quad (12)$$

Contrast improvement coupled with edge enhancement in digital images can be developed by approximating morphological derivatives with discrete differences. A difference of morphological opening and closing yields the image boundary by providing an asymmetric treatment between the image foreground and its background. Local contrast enhancement can be achieved by adding the original image to the difference between morphological open and close transformed image. A two stage iterative morphological filter using variable flat structuring elements is proposed in this work. The flat structuring element used during the first iteration of this filter (15) is a disk shaped structuring element of radius 2 or size 5×5 (13). Similarly the second iteration of this filter (17) utilizes a flat disk shaped structuring element of order 3×3 (14).

$$S_1 = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix} \quad (13)$$

$$S_2 = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \end{bmatrix} \quad (14)$$

1st Iteration:

$$I^{10}(x) = [y(x) \circ R_1] - [y(x) \bullet R_1], \quad (15)$$

$$I^{11}(x) = [I^{10}(x) + y(x)], \quad (16)$$

2nd Iteration:

$$I^{20}(x) = [F^{11}(x) \circ R_2] - [F^{11}(x) \bullet R_2], \quad (17)$$

$$I^{21}(x) = [I^{20}(x) + y(x)], \quad (18)$$

A symmetric flat structuring element of approximately 30 pixels is sufficient to trap brain lesions while smaller sized structuring elements serve to trap small sized features. This justifies the usage of two-stage iterative morphological filter. The duo-iterations of the proposed morphological filter provide significant preservation of the lesion edges along with the removal of noise. This filter has been shown in Fig. 3. The results of the proposed enhancement method are improved in comparison to the morphological top-hat transformation which has been used for fingerprint segmentation [17] as well as for brain tumor detection.

D. Segmentation

After the edges of the tumor have been enhanced by the above proposed filter, segmentation of the targeted abnormality is performed in the ROI. This involves morphological operations of top-hat and bottom hat on the original and enhanced ROI using structuring elements of the size 55, followed by thresholding, as shown in Fig. 4. The result of segmentation provides a more appropriate tumor image with sharp boundaries which helps in accurate analysis and feature extraction of the tumor region.

V. Objective Evaluation of Proposed Method

The ultimate goal of a contrast enhancement algorithm is to reduce distortion in such a manner that some low contrast feature can be visualized by a human observer. It is although difficult to evaluate effectively the effect of image enhancement. *PSNR* (in dB) is a common tool for objective evaluation but it fails to quantify the errors as per the human visual system (HVS) [18]. The degree of contrast improvement provided by the enhancement method is adjudged by the fact that it should enhance the difference between the average gray scale values lying in the background and the foreground regions. *CII*, *PSNR* and *ASNR* are the three quality metrics used in this work for the objective evaluation of the proposed method for contrast and edge enhancement.

A. Contrast Improvement Index (CII)

This parameter for evaluation is performed using the local region of interest (region containing the tumor, referred to as foreground) and the artifacts present in the original as well as the enhanced images. The contrast '*C*' of an object is given by [19]:

$$C = \frac{m_f - m_b}{m_f + m_b} \quad (19)$$

where: m_f is the mean gray-level value of the foreground and m_b is the mean gray-level value of the background. The quantitative measure of contrast improvement, defined as 'Contrast Improvement Index (*CII*)'

$$CII = \frac{C_E}{C_O} \quad (20)$$

where: C_E and C_O are the contrasts of regions of interest in the enhanced and original images respectively. As *CII* does not contain enough information to quantize the background, the two other parameters used are *PSNR* and *ASNR*.

B. PSNR (Peak Signal to Noise Ratio) and ASNR (Average Signal to Noise Ratio)

These parameters are based on general medical physics measurement and accepted by radiologists for detection of abnormalities. *PSNR* and *ASNR* are defined as:-

$$PSNR = \frac{m_f^m - m_b}{\sigma} \tag{21}$$

$$ASNR = \frac{m_f - m_b}{\sigma} \tag{22}$$

Here, σ is the standard deviation, which gives the measurement of the level of noise in the background, m_f^m is the maximum gray level value of the foreground, m_f is the mean gray level value of the foreground and m_b is the mean gray level value of the surrounding background region. Higher the value of *CII*, *PSNR*, and *ASNR*, more promising is the method for contrast and edge enhancement.

VI. Experimental Results

The cerebral magnetic resonance images used for simulation are taken from the 'Whole Brain Atlas' by Keith A. Johnson and J. Alex Becker [20]. This is a registered database which provides the brain image datasets acquired from various techniques; although in this work MR-T2 and MR-GAD images are used for simulation. The contrast of selected ROI is computed by manually selecting the foreground and background with the help of the radiologist markings in the database. The cerebral images obtained from the MRI database are normalized followed by extraction of ROI of size 128×128. The graphical variations of *CII*, *ASNR,* and *PSNR* for various ROI against changes in *k* and *b* are plotted in Fig. 6 and Fig. 7 respectively. The non-linear function parameters *k* and *b* are tuned in such a range yielding high values of quality metrics. Values of enhancement factor (k) $2<k<20$ and control of threshold $0.60<b<0.90$ are optimally chosen in the mentioned bounds to produce visually improved results coupled with high values of quality metrics. The proposed methodology incorporates wavelet decomposition at two levels. Multiple wavelet combinations have been tested and it has been experimentally determined that the daubechies wavelet family yields the most optimal visual results. Hence, DWT has been implemented using daubechies wavelet family at both the levels of decomposition. The selection of wavelets is performed, based on the results mentioned under Table I and results of objective evaluation (*PSNR*, *ASNR,* and *CII*) calculated on different cerebral images using the proposed method are shown in Table II and III respectively. Fig. 8(a) shows the original cerebral MRI and the extracted and preprocessed ROI are shown in Fig. 8(b). Fig. 8(c) shows the enhanced ROI after wavelet reconstruction and Fig. 8(d) shows the edge enhanced and segmented tumor region in ROI after application of morphological filtering modules for edge enhancement and segmentation.

TABLE I: Tabulated Values of *PSNR* for Different Wavelet Combinations

Wavelet Family at Level -1	Wavelet Family at Level- 2	*PSNR*
db2	db2	4.1726
db2	haar	3.6158
haar	haar	4.0929
sym2	sym2	3.6298
db1	db1	4.1677
sym2	db2	9.9623
coif2	coif2	3.2672
haar	db2	3.8384

TABLE III: Tabulated values of *CII* for the proposed enhancement method

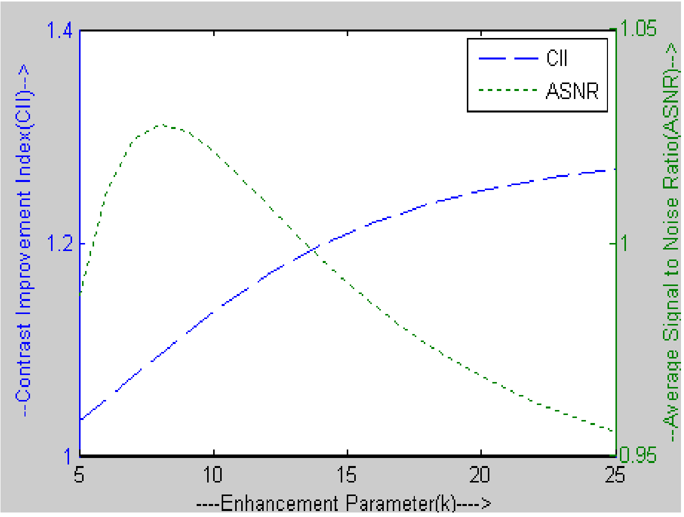
Input Cerebral Images	*CII*	
	After Wavelet Reconstruction	*After Morphological Filter*
I_1	1.2494	1.2933
I_2	1.3826	1.4642
I_3	1.2850	1.3859
I_4	1.1090	1.1859
I_5	1.4825	1.5818
I_6	1.1634	1.3743
I_7	1.4985	1.5471
I_8	1.3183	1.4315
I_9	1.7457	1.8866
I_{10}	3.2975	3.5403
I_{11}	1.9739	2.4740

VII. Conclusion

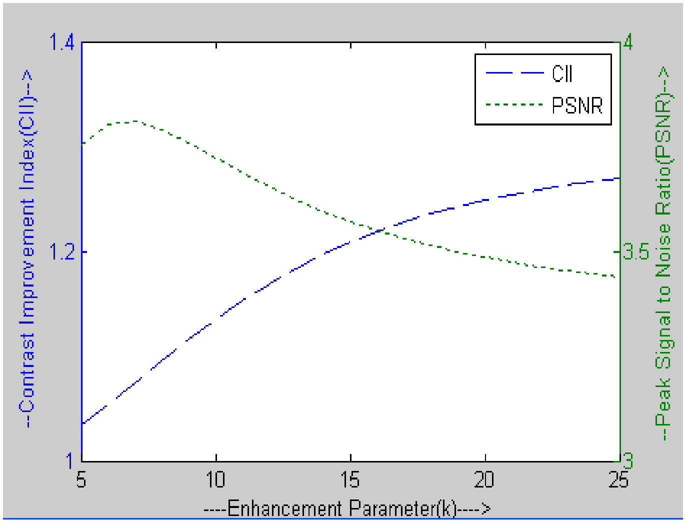
For the proper diagnosis and early stage treatment of brain tumor, a precise study of MRI is the primary requisite. Thus, this paper presents a novel methodology for contrast improvement of cerebral MRI features using combination wavelets and iterative morphological filtering approach. Wavelet transform serves as a powerful tool for image especially with respect to their localization properties in transform domain. The proposed recursive morphological filter uses variable sized structuring elements to enhance the targeted ROI with respect to the non-homogeneous background of the brain tissues. Simulation results show significant improvement in contrast of cerebral features as depicted by increment in the values of the three quality metrics (*CII, PSNR,* and *ASNR*). The segmented tumor is finally obtained with delineated boundaries. The aggregate value of *CII* obtained with the above results is 1.7436 whereas the maximum *CII* reached is 2.3834. However, the average value of *CII* obtained by Kharrat *et al.* [3] is 1.5073, which is less. The proposed framework may lead to precise tumor analysis and feature extraction along with efficient classification at later stages, thereby producing optimization in therapies for the patients suffering from brain tumor.

VIII. Future Work

The performance of the proposed non-linear transformation function can be further increased by applying any mathematical optimization techniques. Features extraction as well as classification of brain anomalies can be done so that the tumor can be classified as benign or malignant. It also seems important to develop algorithms to find optimal number of levels at which wavelet decomposition has to be performed when using soft thresholding and non linear enhancement operator.



(a)



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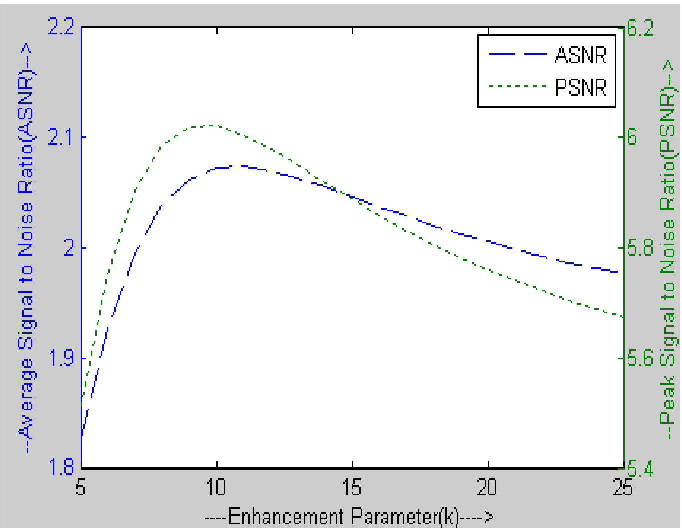
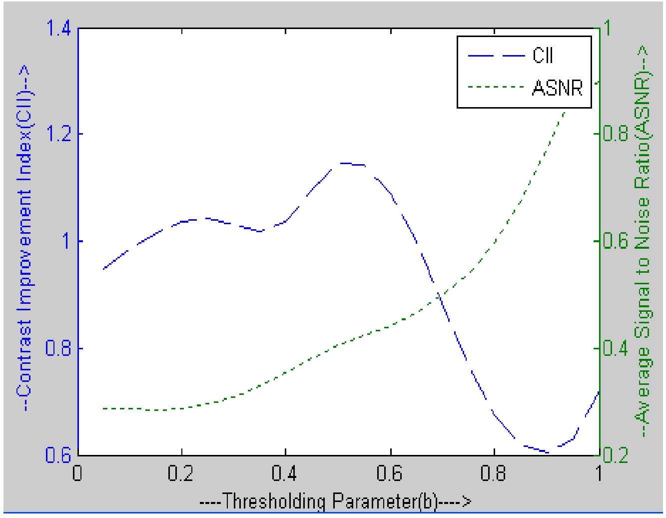
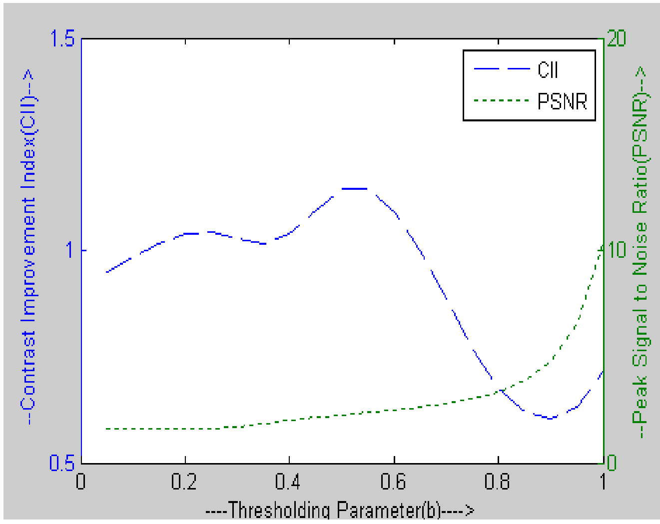


(c)

Fig. 6. **(a)** Graphical variation of *CII* and *ASNR* with against changes in *k*, **(b)** Graphical variation of *CII* and *PSNR* against changes in *k*, **(c)** Graphical variation of *ASNR* and *PSNR* against changes in *k* for image I_1.



(a)



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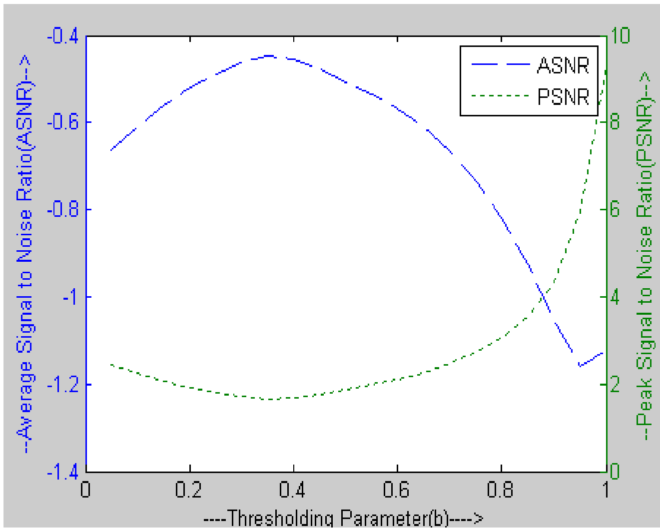
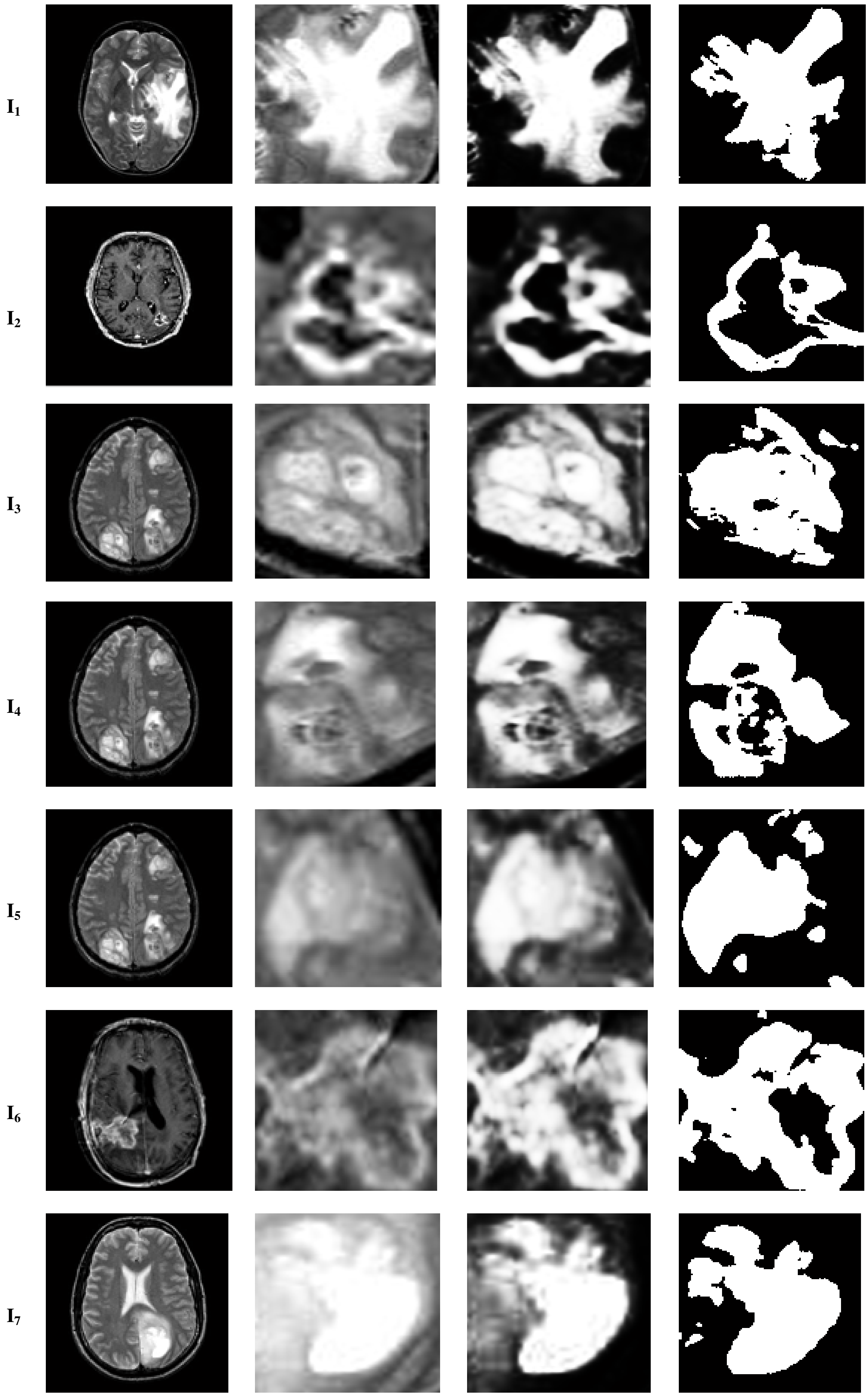


(c)

Fig. 7. **(a)** Graphical variation of *CII* and *ASNR* with against changes in *b*, **(b)** Graphical variation of *CII* and *PSNR* against changes in *b*, **(c)** Graphical variation of *ASNR* and *PSNR* against changes in *b* for image I_1.



I_1
I_2
I_3
I_4
I_5
I_6
I_7

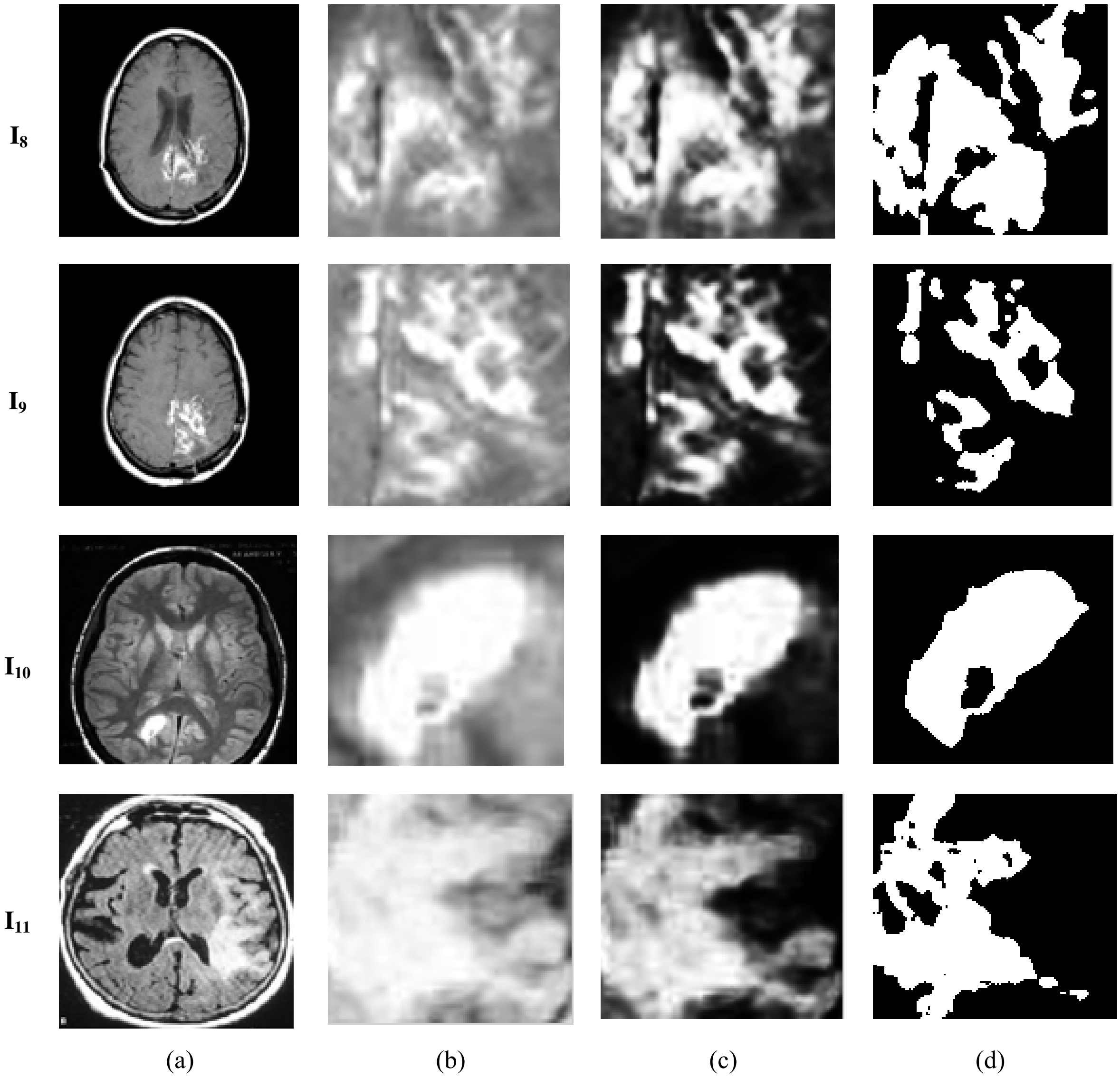


Fig. 8. Enhanced and Segmented MRI images obtained with the proposed methodology. (a) Input cerebral MR images. (b) Preprocessed Region of Interest (ROI). (c) Enhanced ROI after application of wavelet reconstruction. (d) Segmentation of tumor region in ROI.

TABLE II: TABULATED VALUES OF *PSNR* AND *ASNR* FOR THE PROPOSED ENHANCEMENT METHOD

Input Cerebral Images	***PSNR***			***ASNR***		
	Original	**After Wavelet Reconstruction**	**After Morphological Filter**	**Original**	**After Wavelet Reconstruction**	**After Morphological Filter**
I_1	2.1167	2.7327	2.7414	0.8903	0.9232	0.9758
I_2	3.2857	3.4113	3.6895	0.4408	0.5113	0.6090
I_3	2.4987	3.4577	3.6397	1.0744	1.1139	1.1990
I_4	2.0838	2.6032	2.7800	1.4170	1.5331	1.6635
I_5	2.2743	2.4126	2.4866	0.7903	0.8225	0.8707
I_6	2.1547	2.8986	3.0278	1.0220	1.1497	1.2194
I_7	2.7417	5.6898	5.8285	1.9162	2.2859	2.4902
I_8	2.5196	3.1048	3.2749	1.0419	1.1179	1.2369
I_9	2.1270	3.4605	3.5749	0.4902	0.5874	0.6396
I_{10}	3.2859	7.4180	8.9470	1.3987	2.0927	2.6231
I_{11}	1.5185	2.5995	3.0445	0.7997	0.8894	1.0392

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Abhishek Raj is an undergraduate student and is currently pursuing his Bachelor of Technology in Electronics and Communication engineering from Shri Ramswaroop Memorial Group of Professional Colleges, Lucknow (U.P.), India. He will be graduating in July 2011. Currently two of his research papers out of his B.Tech. project work have been selected in international conferences for publication in IEEE and Springer LNCS respectively. He has been awarded the Best B.Tech. Project -2011 award of the college. He is working in the area of biomedical images & signal processing since two years.

Alankrita is in final semester, pursuing B.Tech. (Electronics & Communication Engg.) from Shri Ramswaroop Memorial Group of Professional Colleges, Lucknow (U.P.), India. Recently she has won the second prize for her research paper presentation at the Institution of Electronics and Telecommunication Engineers (IETE) Symposia, conducted by Amity University, Lucknow in February 2011. Her current research includes multimedia signal processing on which recently, she has got two research papers accepted in IEEE conference.

Akansha Srivastava is an undergraduate student pursuing B.Tech. (Electronics & Communication Engg.) from Shri Ramswaroop Memorial Group of Professional Colleges, Lucknow (U.P.), India. She has been a meritorious student working in the area of digital image processing from more than a year. Her current research interests include feature extraction, object recognition, and related topics in signal and image processing.

Vikrant Bhateja has received B.E. (Hons.) Electronics & Communication Engg in 2003 and have recently submitted the thesis work of M. Tech. (in Electronics & Communication Engg.) to Panjab University, Chandigarh. He is an Assistant Professor in Department of Electronics and Communication Engineering, Shri Ramswaroop Memorial Group of Professional Colleges, Lucknow (U.P.) India since 2008. His research interests include digital image processing & computer vision, medical imaging, and neural networks & soft computing. He has more than 20 research publications in national and international conferences.