Segmentation of Brain from MRI Head Images Using Modified Chan-Vese Active Contour Model

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Abstract: In this article, a new segmentation method to extract the brain from T1, T2 and PD-weighted Magnetic Resonance Image (MRI) of human head images based on Modified Chan-Vese (MCV) active contour model is proposed. This method first segment the brain in the middle slice of the brain volume. Then, the brain regions of the remaining slices are segmented using the extracted middle brain as a reference. The input brain image is pre-processed to find the rough brain. The initial contour for the MCV method is drawn at the center of the segmented rough brain image and is then propagated to reach the brain boundary. The result of this proposed method is compared with the hand stripped images and found to produce significant results. The proposed method was tested with 100 volumes of brain images and had accurately segmented the brain regions which are better than the existing methods such as Brain Extraction Tool (BET), Brain Surface Extraction (BSE), Watershed Algorithm (WAT), Hybrid Watershed Algorithm (HWA) and skull stripping using Graph Cuts (GCUT).

Keywords: Brain segmentation, skull stripping, brain extraction method, active contour, magnetic resonance image.

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1. Introduction

Brain segmentation is an essential pre-processing step in neuroimage analysis and eliminates all non-brain tissues such as skull, sclera, fat, skin, eye balls, neck etc, from the Magnetic Resonance Image (MRI) human head scan images. However, this process is difficult because of the presence of various imaging artifacts [23], anatomical variability, varying contrast properties and poor registration among the brain images.

A number of automated and semi-automated skull stripping algorithms are available in the literature [1, 2,4, 5, 6, 7, 10, 11, 12, 16, 17, 18, 19, 20, 24, 25, 26, 27, 31, 32, 33]. Several comparative studies have been carried out on the existing skull stripping methods to analyze their performance using the commonly available datasets [11]. Among all these existing methods, Brain Extraction Tool (BET) [20], Brain Surface Extraction (BSE) [19], Watershed Algorithm (WAT) [7], Hybrid Watershed Algorithm (HWA) [18] and skull stripping using Graph Cuts (GCUT) [17] are the popular methods. Most of the existing automated skull stripping algorithms are devised only to T1weighted Magnetic Resonance (MR) brain images (WAT, HWA and GCUT methods) and may not work well on axial, sagittal and coronal orientations.

Active contour models are widely used in image segmentation field [3, 13, 29]. Chan-Vese (CV) active contour model [3] is one of the well known active contour models, capable to detect both the interior and exterior boundaries of an image. However, the computational complexity is a major overhead for the practical applications of this model, as at each iteration, the CV model requires to compute both the internal and external energy forces for the curve evolution which slows down the process of segmentation. To overcome this, a Modified CV active contour (MCV) model is proposed to extract the brain from MRI head scans. The proposed method based on MCV uses only the internal energy to evolve the curve to detect the fine brain boundary and thus it reduces the computational cost and increases the speed of curve propagation. The experimental results using 100 volumes of T1, T2 and PD-weighted brain images show that the proposed method has produced the best and consistent performance than the popular existing methods such as BET, BSE, WAT, HWA and GCUT.

The remaining part of the paper is organized as follows: In section 2, the original CV model, the proposed MCV method and brain segmentation based on MCV method are described. The results and discussion are given in section 3 and the conclusion is given in section 4.

2. Method

Active contour is a self-regulating dynamic curve that moves under the influence of energy functional towards the desired object boundaries. The basic idea of segmentation using any active contour model starts with an initial closed curve which is iteratively shrunk or expanded with respect to the boundary of the object by satisfying some constraints associated with the image.

2.1. CV Active Contour Model

The CV model without edges is based on Mumford-Shah segmentation techniques [15]. This model is described as a bimodal model, considering the image as a two distinct regions, c_1 (foreground) and c_2 (background) of approximately piecewise-constant distinct intensity values. Given an image u_0 and a closed curve C let c_1 and c_2 be the average intensity of u_0 at the inner region and outer region with respect to C respectively. Then, CV algorithm aims to minimize the energy functional $E(c_1, c_2, C)$ and is defined as:

$$E(c_1, c_2, C) = \mu.Length(C) + v.Area(inside(C)) + \lambda_1 \int_{inside(C)} |u_0(x, y) - c_i|^2 dx dy + \lambda_2 \int_{i} \int_{i} |u_0(x, y) - c_2|^2 dx dy$$
(1)

Where, μ controls the smoothness of zero level set, ν increases the propagation speed, λ_1 and λ_2 controls the image data driven force inside and outside of the contour respectively and, $\mu \ge 0$, $\nu \ge 0$ and λ_1 , $\lambda_2 > 0$ are fixed parameters. Then, the objective of CV model is to find c_1 , c_2 and *C* such that $E(c_1, c_2, C)$ is minimized and is mathematically expressed as:

$$inf_{c_1,c_2,C}E(c_1,c_2,C) \tag{2}$$

2.2. Modified CV Active Contour Model

The CV active contour model has many attractive characteristics such as unrestricted position of the initial curve, automatic detection of interior contours and better segmentation result using global energy minimization approach. However, the computational cost of this method is high because the computation to be done on the same dimension as the image plane.

Thus, the convergence speed is comparatively slower than other segmentation methods, particularly the local filtering-based methods. Also, the original CV model requires more number of iterations to evolve a curve to converge at the boundary and thus it is less desirable for many of the image segmentation applications, where the computational cost and speed are the major concern.

In this proposed method, the original CV model is modified to evolve the curve using the internal energy alone by defining the Initial Contour (IC) to completely lie inside of a region. This MCV active contour model is applied to find the boundaries of MR brain images. In the MCV based brain extraction method, it is enough if the IC is expanded to reach the brain boundary by using only the internal energy and thus the proposed method minimizes the number of iterations and the computational cost involved in the curve evolution process than the CV model. Therefore, the original CV model is modified accordingly and the minimized energy functional E(c, C) is defined as:

$$E(c,C) = \mu.Length(C) + v.Area(inside(C)) + \lambda \int_{inside(C)} |u_0(x,y) - c|^2 dxdy$$
(3)

where, $\mu \ge 0$, $v \ge 0$ and $\lambda > 0$ are the fixed parameters, μ controls the smoothness of zero level set, v increases the propagation speed and λ is the image data driven force inside of the contour. Then, the objective is to

find the minimized E(c, C) It is mathematically modelled as:

$$inf_{c,C}E(c,C)$$
 (4)

2.3. Segmentation of Brain based on MCV Model

The proposed MCV model is developed to evolve the active contour to fit the brain surface of the MR brain images. This method has two-stages. In the first stage, the brain region in the middle slice of the volume is extracted and the brain regions in the remaining slices are extracted in the second stage, based on the shape similarity of the successive slices and the Landmark Circle (LMC) defined in stage-1. The block diagram of the proposed method is given in Figure 1.



Figure 1. Block diagram of the proposed brain segmentation method.

The stage-1 comprises of several operations: Brain image preprocessing, rough brain area selection, fine brain border detection using MCV model and LMC detection in the skull stripped middle slice. The middle slice of the brain volume is first preprocessed to enhance the contrast to obtain the binary image. Sometimes, the performance of the segmentation techniques may be affected due to the intensity nonlinearity introduced by MR imaging devices. Therefore, an automatic contrast adjustment method based on gamma correction [21] is used. After the contrast adjustment, a binary form of the input brain image is obtained using the method given in [22]. Then, the morphological erosion operation is applied to disconnect the non-brain tissues with the brain tissues.

The resultant binary image may contain several holes. Though, the holes in the binary images help to separate the non-brain region from the brain region, sometimes the presence of small holes produce undesirable results during erosion process. Therefore, the small holes are filled using hole filling algorithm [28] before applying the erosion operation. In this method a Structuring Element (SE) of size O_3 as shown in Figure 2 is used for morphological operations.

0	0	1	1	1	0	0	
0	1	1	1	1	1	0	
1	1	1	1	1	1	1	
1	1	1	1	1	1	1	
1	1	1	1	1	1	1	
0	1	1	1	1	1	0	
0	0	1	1	1	0	0	
		-	~				
Figure 2. SE of size O_3 .							

The Largest Connected Component (LCC) in the eroded image is considered as a brain region, because the brain in the middle slice is always larger than the brain in other lower and upper slices in the MR brain slice stack. Then, the selected LCC in the eroded image is dilated to obtain the rough brain mask. In many cases the dilation with the same or less than the size of the SE used for erosion does not restore the original shape of the object [17] therefore the selected rough brain mask. Using the rough brain mask the rough brain mask is again dilated with O_3 to get the rough brain mask. Using the rough brain mask the rough brain area is selected.

The proposed MCV method requires to define an Initial Contour (IC) at the center of the rough brain area to detect the brain border. For this, the radius r is calculated by:

$$r = \frac{1}{2} \left(\frac{\sum d_i}{4} \right) \tag{5}$$

Where d_i is the distance from the center towards its brain border on right, top, left and bottom of the middle brain. Then, the radius *r* is computed by taking the half of the average distance and is then normalized to limit within the minimum value of d_i , so that the computed *r* value will not be greater than any of the d_i values. The normalized *r* value makes the IC to lie completely inside the brain region.



g) LMC on the middle slice brain region (white circle)

Figure 3. Segmentation of brain in middle slice by the proposed method.

After drawing IC on the rough brain area, MCV method is used to evolve the IC to reach the brain boundary. The proposed MCV model able to identify the contour that has smooth boundaries or week edges at lesser number of iterations because it does not depend on gradient information. Then, to accurately select the brain region in the remaining slices of the

brain volume, the IC of the middle slice is used as an LMC and is placed over the segmented middle brain image. This is because the brain regions in the top and bottom slice of the brain volume may contain more than one region. Then, the regions in the segmented image which are partially or fully overlap with LMC are selected as brain regions and the rest are discarded. Figure 3 illustrates the process involved in stage-1 of the proposed method.

The stage-2 consists of several operations such as brain image preprocessing, rough brain area selection, brain boundary detection by MCV method and fine brain regions selection based on LMC. This method starts from the middle slice and then move towards the lower and upper slices to extracts the brain regions from all the slices of the volume. The brain segmentation process of stage-2 is presented in Figure 4.



Figure 4. Segmentation of brain in remaining slices.

As similar to that of stage-1, each brain slice in stage-2 is also required to preprocessed using the methods [21, 22] to obtain the binary image. Then the rough brain in the binary image is selected by combining all the regions which overlap with the previous brain mask BM. Then, the Percentage of Overlap (PO) is calculated by Equation 6 to measure the shape similarity between the current rough brain and the previous brain mask.

$$PO(g_{RBM}, BM) = \frac{T(g_{RBM} \zeta BM)}{T(g_{RBM})} \times 100$$
(6)

Where T(X) is the total number of pixels in the image X. In general, the adjacent brain slices have approximately similar shape and size. If the computed *PO* is greater than 90% then the g_{RBM} is similar in

shape to that of the previous adjacent brain mask. Lesser percentage of *PO* denotes that the selected g_{RBM} may contain some connected non-brain regions and the morphological erosion operations are used to disconnect these non-brain regions.

Sometimes, the erosion operation may fail to separate these regions which have weak edge between the brain and non-brain tissue. For such a slice, the same previous brain mask BM is used as g_{RBM} and is given by:

$$g_{RBM}(x, y) = \begin{cases} 1 & \text{if } BM(x, y) = 1 \\ 0 & \text{otherwise} \end{cases}$$
(7)

To recover the brain pixels lost, the selected g_{RBM} is dilated again by O₃. Then the brain border in g_{RBM} is detected by applying the proposed MCV border detection technique. Often the brain in the top and bottom slices of axial and coronal oriented head scan volumes may contain more than one connected regions. In order to select all the brain regions accurately on these slices, the LMC defined in stage-1 is used. Then, the fine brain regions are selected by finding the regions which partially or fully overlap with the LMC. The step involved in proposed twostage skull stripping method is given in Algorithm 1.

Algorithm 1: The proposed two- stage method

STAGE-1

Input: Middle slice of the brain volume. Output: Segmented brain image of the middle slice.

- 1. Let f be the middle slice of the brain volume.
- 2. Enhance the contrast of the input brain image f to get f^4 .
- 3. Obtain the binary image of f^{A} to produce g.
- 4. Fill the small holes in g.
- 5. Select LCC after applying morphological erosion operation on g.
- 6. Obtain the rough brain mask.
- 7. Get the rough brain image.
- 8. Define the initial contour.
- 9. Find the brain border image using MCV method.
- 10.*Obtain the fine brain image.*
- 11.Define the LMC.

STAGE-2

Input: MRI head scan volume and LMC of middle slice. Output: Segmented brain volume.

- 12.Let N be the total number of slices in the brain volume. Let M be the middle slice of a volume. Assign L=M-1and U=M+1.
- 13.*Repeat Steps* (i)-(vii) towards the backward direction (from L to 1) and then in forward direction (from U to N) until the brain in all the slices are segmented.
- 1. Let g be the gamma corrected binary form of the current input slice. Let BM be the brain mask of the previous adjacent slice.
- 2. Obtain the rough brain mask g_{RBM} using g and BM.
- 3. Find the rough brain.
- 4. Define the initial contour inside the rough brain.
- 5. Find the fine brain border by MCV method.
- 6. Obtain the fine brain mask by finding the intersecting

regions with LMC defined in Stage-1. 7. *Output the segmented brain image.*

7. Output the segmented brain thage.

2.4. Performance Evaluation Metrics

The performance of the proposed method is measured using Jaccard similarity index (J), Dice coefficient (D), False Positive Rate (FPR) and False Negative Rate (FNR) [26]. The Jaccard similarity index (J) and the D are given by:

$$J(S_1, S_2) = \frac{|S_1 \cap S_2|}{|S_1 \cup S_2|}$$
(8)

$$D(S_1, S_2) = \frac{2|S_1 \cap S_2|}{|S_1| + |S_2|}$$
(9)

Where, S_1 denote the total pixels of the image obtained by the proposed method and S_2 denote the total pixels in the image obtained from hand stripped image data.

The positive and negative misclassification [1] done by the proposed method is measured by *FPR* and *FNR*. *FPR* is the ratio of the number of pixels incorrectly classified as brain region to number of non-brain region and false positive pixels. *FNR* is the ratio of the number of pixels incorrectly classified as non-brain region to number of brain region and false negative pixels. The *FPR* and *FNR* are calculated by:

$$FPR = \frac{|FP|}{|TN| + |FP|} \tag{10}$$

$$FNR = \frac{|FN|}{|TP| + |FN|}$$
(11)

Where TP is true positive which represents the number of voxels correctly classified as brain tissue by the proposed method and FP is false positive which represents the number of voxels incorrectly classified as brain tissue by the proposed method. TN and FN are true negative and false negative, which are defined as the number of voxels correctly and incorrectly classified as non-brain tissue by the proposed method.

2.5. Datasets Used

2.5.1. T1-Weighted Brain Volumes

Sixty volumes of T1-weighted brain images from dataset-1 and dataset-2 were used to evaluate the performance of the proposed method. Dataset-1 has 20 volumes of T1-weighted images of young-middle aged normal individuals obtained from Internet Brain Segmentation Repository (IBSR) [9]. Each volume consists of 2D sequential coronal slices with dimensions of 256x256 pixels with the slice thickness is 3.1 mm and the number of slices ranges from 60 to 65.

The dataset-2 contains 40 volumes of T1-weighted brain images obtained from Laboratory of Neuroimaging (LONI) [14]. It consists of 20 male and 20 female subjects, ages varying from 19 to 40 years and the mean age is 29.2 years. The dimension and inter slice gap are $256 \times 256 \times 124$ and $0.86 \times 0.86 \times 1.5$ mm³/voxel for 38 subjects, $256 \times 256 \times 120$ and $0.78 \times 0.78 \times 1.5$ mm³/voxel for 2 subjects respectively.

2.5.2. T2-Weighted Brain Volumes

This method was experimented using dataset-3 consisting of twenty volumes of normal and abnormal T2-weighted brain volumes collected from WBA [30]. Each volume consists of axial slices with dimensions of 256×256 pixels and the slice thickness varies from 2-5mm with 260mm field of view. The number of slices ranges from 18 to 56.

2.5.3. PD-Weighted Brain Volumes

Twenty volumes of PD-weighted normal and abnormal subjects (Dataset-4) used in this experiment were collected from the WBA [30]. Each volume consists of axial slices with dimensions of 256×256 pixels. The slice thickness varies from 2-5mm with 260mm field of view. The number slices ranges from 17 to 55.

3. Results

The performance of the proposed brain segmentation method was evaluated using 100 volumes of T1, T2 and PD-weighted brain images obtained from dataset-1 to dataset-4 and are compared with the existing methods BET, BSE, WAT, HWA and GCUT. The summary of the various parameters setting for the existing methods and the proposed method are given in Table 1.

Table 1. Parameters setting for the existing methods BET, BSE, WAT, HWA, GCUT and the proposed method.

Method	Fixed Parameters	Value	Input Image Type	
BET	Fractional intensity threshold threshold gradient	0.5	T1,T2 and PD-weighted	
BSE	Diffusion iteration Diffusion constant Edge constant Erosion size	35 0.62 2	T1, T2 and PD-weighted images	
WAT	Pre-flooding height	$h_{\rm pf}=0.11 \ I_{\rm max}+3.5n$	T1-weighted images	
HWA	Pre-flooding height Post watershed threshold	25% of <i>I_{max}</i> 3√vol(basin)	T1-weighted images	
	Curvature range Atlas-based force constants	r_{min} =3.33, r_{max} =10 λ_D =0.25, λ_C =0.025		
	Convergence threshold	0.5 mm		
CCUT	Intensity threshold for white mater	0.36	T1-weighted	
GCUI	Intensity control parameter	2.3	images	
Proposed	Overlapping ratio SE for erosion SE for dilation Small hole size Modified CV constants Maximum number of	90% O ₃ O ₃ 25 pixels μ=0.2, v=0 and λ=1 100	T1,T2 and PD-weighted images	
	Maximum number of iterations	100 100		

The parameter setting for the proposed method is estimated after executing it on several volumes of brain images. The BET, WAT, HWA and GCUT were used with default parameter values. For the existing method BSE, the default parameter values were changed as suggested by [8].

The performance comparison of the brain boundary detection by the original CV and the proposed MCV method on some selected sample T1, T2 and PDweighted images are shown in Figure 5. In Figure 5-a, images 1 and 2 are T1-weighted images, Image 3 is a T2-weighted and image 4 is a PD-weighted image. The initial contours (red circles) for the CV and MCV active contour methods are defined and are shown in Figure 5-b. The detected brain boundaries are drawn as red curves on the rough brain images using CV and MCV methods and are illustrated in Figures 5-c and 5d respectively. The number of iterations needed to reach the brain boundary for CV and MCV methods are given under each image in the Figures 5-c and 5-d respectively. From Figures 5-c and 5-d it is noted that, the original CV method requires almost the maximum number of iterations (i.e., 300 iterations) to evolve the curve, however the MCV method needs less number of iterations and it is about 10 times faster than the original CV model to detect the brain boundaries in all the brain images of the datasets used.



Figure 5. Brain boundary detection by CV and MCV methods.

The brain volumes of dataset-1 to dataset-4 are converted from their original orientation into other orientations and the efficiency of the proposed method on different image orientations (coronal, sagittal and axial) are tested and are compared with the existing conventional BET and BSE methods. The skull stripping results obtained for some of the selected sample images of dataset-1 by BET, BSE and the proposed methods are shown in Figure 6. For these selected images, the BET under-segments them by including the non-brain regions whereas BSE oversegments the brain by omitting some brain tissues. Thus, it is clear from Figure 6 that the proposed method is adaptable to different image orientations than the conventional BET and BSE methods.



Figure 6. Skull stripping results by the existing and proposed methods on all the orientations.

The quantitative performance of the proposed method was evaluated by calculating D, J, FPR and FNR for the images of dataset-1 and dataset-2 using the Equations 8, 9, 10 and 11. To compare the performance of the proposed and the existing methods (BET, BSE, WAT, HWA and GCUT) for dataset-1, the computed mean, Standard Deviation (SD) and range for the parameters D, J, FPR and FNR are given in Table 2.

Table 2. Computed values of mean, SD and range for the parameters *D*, *J*, *FPR* and *FNR* by BET, BSE, WAT, HWA, GCUT and the proposed methods for dataset-1

Measures		Methods						
		BET	BSE	WAT	HWA	GCUT	Proposed	
D	Mean	0.74	0.79	0.76	0.78	0.85	0.97	
	SD	0.14	0.14	0.14	0.21	0.09	0.006	
	Rang	0.52.0.00	0-0.95	0.47-0.92	0.16-0.88	0.49-	0.95-	
	e	0.55-0.90				0.90	0.98	
J	Mean	0.61	0.69	0.64	0.68	0.75	0.94	
	SD	0.18	0.22	0.18	0.21	0.10	0.01	
	Rang	0.26.0.91	0-0.90	0.31-0.86	0.09-0.78	0.33-	0.91-	
	e	0.30-0.81				0.81	0.96	
FPR	Mean	79.9	5.1	18.4	131.2	38.3	0.35	
	SD	59.3	3.1	14.1	308.2	40.1	0.002	
	Rang	22.7-	2 1 12 0	5.2-61.2	19.4-	23.1-	0.001-	
	e	179.4	2.1-13.0		1060.2	207.5	0.008	
FNR	Mean	0.1	27.0	24.5	1.9	0.01	4.12	
	SD	0.1	24.1	22.7	6.5	0.02	0.01	
	Rang 0.0 0.4	2 5 100	0 1 62 7	0.0 28.0	0.0-	0.02-		
	e	0.0- 0.4	5.5-100	0.1-02.7	0.0- 20.9	0.06	0.06	

It can be seen from the Table 2 that the proposed method gives the average value of D=0.97 and J=0.94. The better *FPR* (%) of 0.35 was produced by the proposed method compared to other methods. The better *FNR* (%) is recorded by GCUT method. The existing methods have produced lower similarity measures due to the homogeneous appearance of brain and non-brain tissues on several volumes of Dataset-1. However, the proposed method has produced a better and consistent performance using the same dataset.

The performance of the proposed method on dataset-2 was evaluated by computing D, J, FPR and FNR values and compared with the values obtained by BET and BSE methods is known in Table 3. The proposed and BET methods have produced consistent results on all the volumes of Dataset-2, while BSE has produced the best average D and J values of 0.96 and 0.93 respectively though it has failed to extract the brains in the volumes labelled 'S23' and 'S32'. For the same volumes, the proposed method has produced better value of D=0.92 and J=0.84 for 'S23' and D=0.94 and J=0.88 for 'S32' respectively. The better FPR (%) value of 1.26 was achieved by the proposed method compared to other methods.

Table 3. Computed values of mean, SD and range for the parameters D, J, FPR and FNR by BET, BSE and the proposed method for dataset-2.

Measures		Methods					
		BET	BSE	Proposed			
	Mean	0.962	0.966	0.948			
D	SD	0.01	0.01	0.01			
	Range	0.93-0.98	0.77-0.99	0.91-0.97			
J	Mean	0.928	0.937	0.902			
	SD	0.02	0.01	0.02			
	Range	0.87-0.95	0.64-0.99	0.82-0.94			
FPR	Mean	4.7	1.96	1.26			
	SD	0.001	0.001	0.007			
	Range	0.0005-0.0443	0.0095-0.2078	0.0030-0.0351			
FNR	Mean	5.95	1.12	5.91			
	SD	0.02	0.01	0.02			
	Range	0.0200-0.1002	0.0005-0.0387	0.0017-0.1541			

The qualitative performance of the proposed method on T2 and PD-weighted images were evaluated using dataset-3 and dataset-4 (since repository of these volumes does not contain hand-stripped volumes) and the segmentation results on selected sample volumes are shown in Figures 7 and 8 respectively. Figure 7 shows a T2-weighted abnormal brain volume of 27years-old man containing 23 slices superimposed with the boundary of the brain regions extracted by BET, BSE and proposed method. Figure 8 represents the brain boundary extracted by BET, BSE and proposed method on PD-weighted abnormal brain volume of 45years-old female containing 24 slices affected with acute stroke.



Figure 7. A T2-weighted brain volume of abnormal subject from dataset-3 superimposed with brain extraction result outlined in red line by BET, blue line by BSE and yellow line by the proposed method

After experimenting the proposed method on all the volumes of T2 and PD weighted images, it is observed that both the existing methods BET and BSE have failed to detect the brain boundaries accurately on all these volumes. It is clear from the results of proposed method that the skull stripping potential of this technique is better than the other two methods BET and BSE on T2 and PD-weighted volumes. Moreover, it is found to be robust on both normal and abnormal brain images of different types and orientations.



Figure 8. A PD-weighted brain volume of abnormal subject from dataset-4 superimposed with brain extraction result outlined in red line by BET, blue line by BSE and yellow line by the proposed method.

Although, this proposed method gives consistent performance for the brain images having Intensity Non-Uniformity (INU) artifact, varying image contrast and works well on all the slices with complicated structure like neck, eyes and other non-brain tissues.

For a few slices, it has failed to extract the brain regions due to the intensity similarity between the brain and non-brain tissues that may have weak edges and hence the process of curve evolution could not be stopped on reaching the desired contour and thus it grows beyond the boundary, covering the non-brain tissues/regions. The similar result were also obtained on the existing skull stripping methods BET and BSE on the same set of brain images shown in Figure 9 on which the proposed method had failed.



Figure 9. Under/over-segmentation by the existing and the proposed methods.

4. Conclusions

The MCV method presented in this paper is developed to detect the brain boundaries accurately in MR brain images. The performance of the proposed MCV based brain segmentation method was tested on T1, T2 and PD-weighted normal and abnormal MRI head scan volumes and it was found that this method produces better results in lesser number of iterations than the original CV method. The results of the proposed method substantiate the robustness on the normal and abnormal brain image slices of different types and orientations.

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