A novel Skull Stripping Method for T1 Coronal and T2 Axial Magnetic Resonance Images of Human Head Scans Based on Resonance Principle

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Abstract - In this paper we propose a novel method for skull stripping or brain extraction from T1 Coronal and T2 Axial Magnetic Resonance Images (MRI) of human head scans. Brain extraction is done by first detecting the boundary separating brain tissue and non-tissues. The pixel values at the bright boundary will be ≈ 255. This property is utilized to generate resonance behaviour at the boundary. We make use of the exponential function to generate the resonance condition using which the boundary is detected. Using the boundary, the skull portion is removed and the brain is extracted. The experiments on two T1 and a T2 volumes show satisfactory results.

Keywords: Skull stripping, segmentation, resonance method, MRI processing

1 Introduction

Magnetic resonance image (MRI) analysis is a non-invasive, non-ionising and non-destructive imaging technology to study the structural anatomy of human organs. This can produce high quality and highly detailed images, which can almost give every angle of organs and tissues. MRI of the brain gives the anatomy of brain that is helpful to diagnose the brain related diseases. MRI guided surgery like angiogram, breast biopsy is directed accurately after knowing the result of brain related diseases. The volume due to the 3D nature of the region growth. The method proposed by Adams et al.[2] requires the input value for the number of seeds, either individual pixels or regions, which controls the formation of regions into which the image will be segmented. Brummer et al.[3] proposed a fully automatic algorithm that starts with a histogram-based thresholding preceded by an image intensity correction procedure. This step is followed by a morphological operations which refines the binary mask images. Anatomical knowledge essential for the discrimination between desired and undesired structures is implemented in this step through a sequence of conventional and novel morphological operations, using 2-D and 3-D operations. The final step of the procedure performs overlap test between current and previous slice. Lemieux et al.[4] proposed an automated algorithm to segment the brain portion from T1-weighted volume MRI. The algorithm uses automatic computation of intensity threshold and morphological operations. It is a three-dimensional method and therefore independent of scan orientation. Hohne et al.[5] proposed a semi-automated segmentation algorithm based on region growing and morphological operations. This segmentation is performed concurrently with 3D visualization providing direct visual feedback to guide the user in the segmentation process. Jong and Lee.[6] proposed an algorithm, after eliminating the background voxels using histogram analysis. Two seed regions of the brain and non-brain regions were automatically identified using a mask produced by morphological operations. Then these seed regions are expanded with a 2D region growing algorithm based on general brain anatomy information. An automatic method for brain extraction was proposed by and Stella et al.[7]. This method uses an integrated approach which employs image processing techniques based on anisotropic filters, snake contouring technique, and a priori knowledge, which is used to remove the eyes, a tricky structure in brain MRI. It is a multistage process, involving removal of the background noise leaving a head mask, finding a rough outline of the brain and refinement of the rough brain outline to a final mask. In an earlier work[8] we used Ridler’s method, morphological operations to extract brain from T2 weighted MRI.

In this paper we propose a brain extraction scheme using resonance method to detect brain-skull boundary. The remainder of the paper is organized as follows. In section 2,
we present our method. In section 3 results and discussions are given. In section 4 the conclusion is given.

2 Proposed Method  
2.1 Skull – Brain Interface  
We model the skull-brain boundary as an interface of two regions. It is well known, at the interface of two media, interfacial waves propagate along the boundary. The amplitude of such waves remain constant along the interface boundary and decay exponentially in a direction perpendicular to the interface. In a plane geometry, at the interface of water-air, hydrodynamic surface waves propagate along the interface with constant amplitude [9], but decay exponentially in a direction perpendicular to the interface.(see Fig.1).

Fig.1 Decay of amplitude in an interfacial wave.

Hydromagnetic interface waves propagate in a similar way in a plasma-plasma interface embedded in a magnetic field [10]. We make use of a similar property to detect the boundary between skull-brain interface. At the boundary, made of white pixels, the intensity value will be ≈ 255 in a gray scale image. Therefore, the boundary can be detected by using the resonance function:

\[ R(x,y) = A \cdot e^{\frac{1}{\Delta f(x,y)}} \]  

Where, \( A \) is an arbitrary constant, \( \Delta f(x,y) = 255 - f(x,y) \), and \( f(x,y) \) is the intensity value of the input image at the co-ordinate points \( (x,y) \). Therefore, \( R \) will be very large (resonance condition) at the boundary, where \( f(x,y) \approx 255 \) and will be small at the points away from the boundary. Hence by computing the value of \( R \) and traversing the co-ordinates \( (x,y) \) where \( R(x,y) \) gives highest value, the boundary of the brain-skull can be identified and extracted.

2.2 Brain Boundary Detection  
In MRI of head scans, two boundaries prominently appear. The inner boundary is the brain-CSF (Cerebro spinal fluid) interface, and the outer boundary is the CSF-Skull boundary(Fig.2). If we are able to detect the inner boundary then the brain portion can be extracted easily.

Fig.2 The prominent boundaries in MRI.

To detect the inner boundary we start computing the resonance function \( R \) from the mid point of each row of the middle slice. Since in both T1 and T2 MRI volumes, the middle slice contains the brain as a single largest region. Hence identifying the brain area in the middle slice is easy. The mid point of each row is computed by dividing the total width and height of the image by 2.

\[ \text{midx} = \text{image\_width}/2 \]  
\[ \text{midy} = \text{image\_height}/2 \]  

Hence the process starts from the midpoint to get the seed point which is the first occurrence of the resonance(R) on both sides from mid point. We repeat this process for each row for the whole image. The closely placed inner most resonance points (CPP) are connected to form a boundary. The boundary will be formed by analysing the value of \( R \) at 5 co-ordinate points at each row in both left and right hand side from the middle. The points that are not close to the innermost boundary are discarded. The innermost contour thus formed is the boundary of the brain. The flow chart of our scheme is given in Fig.3.

![Flow chart showing the process of brain boundary detection](image)
In any MRI brain volume, the middle slice contains brain as a single largest region and is the largest brain portion in the entire volume. Hence identifying the brain area in the middle slice is easy. After finding the brain in the middle slice, the extracted brain portion of the middle slice is used as a reference to extract brain portion from adjacent slices lying above and below it. We then move from middle slice to top and middle to bottom slice, one direction at a time. For each slice, the mark of the previous slice is used as a reference to extract brain in the current slice.

3 Results and Discussions

3.1 Materials Used

For our experiments we used three MRI volumes. The first two are T1 weighted coronal datasets collected from International Brain Segmentation Repository (IBSR)[15] maintained by Center for Morphometric Analysis Massachusetts General Hospital, USA (1_24 and 13_3). The third is a T2 weighted axial MRI dataset collected from Whole Brain Atlas(WBA).[16] maintained by Department of Radiology and Neurology at Brigham and women’s hospital, Harvard Medical school, Boston, USA. T1 weighted 1_24 data set contains 65 slices and 13_3 data set contains 57 slices. Slice thickness = contiguous 3.1mm and each of 256*256 pixel size. T2 weighted dataset contains 56 slices. slice thickness ≈ 5mm and each of 256*256 pixel size. For each dataset, the hand segmented brain portion or gold standard is available in the respective websites.

In the IBSR T1 1_24 dataset brain portions will not be available after 55th slice, but our method detect a small part in 61 and 62 as brain portion. In the WBA T2 dataset brain portion is absent after 50th slice. Our method is not able to detect brain portion in 50th slice, because the brain portion appears in multiple parts, where as the skull contains closely placed pixels with good intensity values. After 50th slice brain portions will not be available.

3.2 Performance Evaluation

We carried out experiments by applying our method on the Three volumes of T1 and T2 weighted images. For performance evaluation of our method we made quantitative and qualitative analysis. For quantitative analysis we computed Jaccard and Dice coefficient similarity indices.

The Jaccard coefficient is given by[17]:

\[ J(A,B) = \frac{|A \cap B|}{|A \cup B|} \]  

(4)

The Dice coefficient is given by[18]:

\[ D(A,B) = \frac{2|A \cap B|}{|A| + |B|} \]  

(5)

where, A is a data segmented using our method and B is hand segmented data. The value of J and D vary between 0 to 1. The best results will be very close to 1, when both results are similar. The computed values of J and D using the proposed method and that of Brain Extraction Tool(BET).[19] are given in Table 1. The best values are given in bold. We observe from Table 1 that our method gives better results than that of the popular method BET.

<table>
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<tr>
<th>DataSet</th>
<th>BET</th>
<th>Proposed method</th>
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<tbody>
<tr>
<td></td>
<td>Jaccard</td>
<td>Jaccard</td>
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<tr>
<td>T1 1_24</td>
<td>.9459</td>
<td>.9722</td>
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<tr>
<td>T1 13_3</td>
<td>.9453</td>
<td>.9615</td>
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<tr>
<td>T2</td>
<td>.9531</td>
<td>.9760</td>
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For visual inspection we also give the brain portion extracted using our method. For visual comparison we give original images, extracted brain portion by BET and by our method.

Fig.4 shows the original slices of T1 weighted coronal 1_24 dataset. Fig.5 brain portion extracted from the dataset 1_24. Fig.6 shows the original slices of T2 weighted dataset. Fig.7 shows the extracted from dataset of T2 weighted axial image from 9th slice to 48th slice. Fig.8 shows BET slices of containing regions like neck and skull portions and extracted brain portions by our method.

![Flow Chart of the Proposed Method](image-url)
Fig. 4 The original slices of T1 weighted coronal dataset 1_24.
Fig. 5 Extracted brain portions from T1 weighted coronal 1_24 by our method.
4 Conclusions

We have proposed a novel method based on interfacial resonance phenomena to extract brain portion from T1 coronal and T2 axial MRI of head scan images. This method is able to detect the boundary of brain skull directly and thus avoids the processing of background and skull areas. The proposed method gives better results in terms of the Dice and Jaccard co-efficients for both T1 and T2 Images than that of popular method BET.
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5 References


[15] International Brain Segmentation Repository, Center for Morphometric Analysis Massachusetts General Hospital, CNY-6, Building 149, 13th Street, Charlestown, MA, 02129-USA. http://www.cma.mgh.harvard.edu/ibsr/ibsr_data/sec3_sub2.html


