A Simple Skull Stripping Algorithm for Brain MRI

Shaswati Roy
BIB Lab, Machine Intelligence Unit
Indian Statistical Institute, Kolkata, India
E-mail: shaswatiroy_t@isical.ac.in

Pradipta Maji
BIB Lab, Machine Intelligence Unit
Indian Statistical Institute, Kolkata, India
E-mail: pmaji@isical.ac.in

***Abstract*—The skull stripping method is an important area of study in brain image processing applications. It acts as preliminary step in numerous medical applications as it increases speed and accuracy of diagnosis in manifold. It removes non-cerebral tissues like skull, scalp, and dura from brain images. In this regard, a simple skull stripping algorithm, termed as S3, is proposed in this paper, which is based on brain anatomy and image intensity characteristics. The proposed S3 method is unsupervised and knowledge based. It uses adaptive intensity thresholding followed by morphological operations, for increased robustness, on brain magnetic resonance (MR) images. The threshold value is adaptively calculated based on the knowledge of intensity distribution in brain MR images. Experimental results, both qualitative and quantitative, are reported on a set of synthetic and real brain MR T1-weighted images. The performance of the proposed S3 algorithm is compared with that of three popular methods, namely, brain extraction tool (BET), brain surface extractor (BSE), and robust brain extraction (ROBEX) using standard validity indices.**

Keywords*—*Magnetic resonance imaging, skull stripping, thresholding, mathematical morphology.

I. Introduction

MAGNETIC resonance imaging (MRI) is based on the detection of various magnetic properties of the protons of hydrogen atoms in the human body, when placed within magnetic field. It is a safe modality and important diagnostic imaging technique for the early detection of abnormal changes in tissues and organs, and therefore, majority of research in medical imaging concerns MR images [1]. Conventionally, the brain MR images are interpreted visually and qualitatively by radiologists. The most important advantage of MRI is the ability to provide high spatial resolution.

The skull stripping method is the process of removal of non-brain tissues, like skull, scalp, dura, eyes, etc. from brain MR images. It is used as an important preprocessing step in many brain MR image processing applications. This method of identifying brain matter plays a vital role in segmentation of brain tissues, pathology detection, multi-modality brain image registration, and so forth. For example, during segmentation of brain tissues, the skull stripping algorithm is incorporated to identify the region of interest. As a result, it reduces the misclassification of brain tissues during segmentation which, in turn, improves the segmentation accuracy as well as minimizes the execution time of segmentation algorithm by eliminating the objects for non-cerebral tissues.

Several methods for brain and non-brain segmentation have been proposed in the literature. There are four broad categories of automated skull stripping algorithms proposed so far: region growing [2], [3], [4], deformable surface model [5], [6], and thresholding with morphology [7], [8] and hybrid approaches [9], [10], [11]. The region growing methods group sub-regions into larger regions depending on some predefined criteria. One disadvantage is that the success of the skull removing methods using region growing approaches relies on the seed selection which may be given manually [2] or by any seed selection algorithm which automatically selects seeds corresponding to the brain and non-brain regions.

In the methods using deformable surface model, a surface model is defined and is then fitted to the brain surface in the image by iteratively deforming the surface from its initial position until an optimal solution is found. Smith [6] developed a brain extraction method, termed as BET, which uses a deformable model that evolves to fit the brain surface by the application of a set of locally adaptive image forces. A triangular tessellation of a sphere's surface is initialized inside the brain and allowed to slowly deform, one vertex at a time. Prior to the application of the surface model, different brain parameters are estimated. The method is very fast and requires no preregistration or other pre-processing before being applied. But, the BET may over-estimate the brain boundary of brain MR images [6]. Also these deformable surface model approaches are sensitive to noise factors and quality of initial contours.

In case of skull stripping using thresholding with morphology, initial segmentation of brain and non-brain regions is achieved based on intensity thresholding. Then the binary mask is obtained by subsequent application of different morphological operations. Since the morphology operations need binarization of the image, selection of a threshold value is crucial to generate the mask for brain tissues, in turns, to ensure the accurateness of diagnosis.

Hybrid methods improve robustness by combining some of the above techniques. Shattuck and Leahy [9] proposed the brain surface extraction methodology, termed as BSE, which combines anisotropic diffusion filtering as a denoising step prior to edge detection, and morphological operations. The stripped brain is then processed to correct for image non-uniformities by analyzing histograms of small neighborhoods of voxels in the image based on a parametric tissue measurement model. But, this background and foreground corrections are restricted to lie within a plane, which means that larger corrections are not likely to follow anatomical boundary. A second drawback of the approach is that the final results depend on the initial orientation of the volume. Moreover,

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the BSE requires parameter adjustment to obtain satisfactory results for different data sets used. Ségonne et al. [10] developed brain segmentation by combining watershed techniques to approximate the initial contour and a deformable surface model to fit the contour accurately to the brain boundary. Finally, the atlas, compiled from a set of segmented brains, is used to verify the shape of the brain surface and to correct it if needed. But, this method often is prone to under segmentation. Iglesias et al. [11] proposed learning-based brain extraction system, termed as ROBEX, which combines discriminative random forest classifier trained to detect the brain boundary and a generative point distribution model to find the contour with highest likelihood according to the classifier. Finally, the contour is refined using graph cuts. The main disadvantage with ROBEX is that it does not produce segmentations as sharp as BET or BSE. In brains with very convoluted surfaces, this method leads to the inclusion of dura and/or gray matter loss. For the same reason, ROBEX fails to provide a very accurate segmentation at the posterior region of the cerebellum-cerebrum interface.

Thus any skull stripping algorithm does not seem to extract the brain tissues from brain MR images accurately without initialization of parameters and high execution time. According to Somasundaram and Kalaiselvi [12], fully automated skull stripping methods should have the capability to extract the brain accurately from a large database of T1-weighted MRI of head scans without any user intervention. Furthermore, the procedure should not take any preprocessing help from any non-image processing routines. In this regard, the paper presents a new skull stripping algorithm S3 that adaptively computes threshold value to initially segment the input brain image into brain and non-brain regions, followed by morphological filtering to obtain a smooth brain mask. Computation of the threshold value is based on the knowledge of intensity distribution of brain and non-brain tissues in brain MR images. Finally, morphology operations, opening and closing, are used to increase the robustness of the method. The performance of the proposed method, along with the related existing skull stripping methods, BET, BSE, and ROBEX, is extensively studied on a set of both synthetic and real brain MR images qualitatively and quantitatively using standard segmentation validity metrics. The flow of this paper is as follows. Section II discusses about the proposed methodology. Section III presents the experimental results obtained on synthetic as well as real brain MR volumes using standard validity indices. Finally, it is concluded in Section IV.

II. Proposed Segmentation Methodology

The basic assumption of the proposed method is that white matter is surrounded by darker gray matter and even darker cerebrospinal fluid (CSF) in T1-weighted brain MR images. The membrane at brain surface that borders the brain matter has darker intensity values than that of skull and CSF. It is also assumed that the brain region is larger than the skull portion.

The proposed skull stripping algorithm S3 consists of a sequence of steps. Before applying the binary mathematical morphology operations, this method initially segments the image into brain and non-brain regions using the threshold value computed adaptively from image intensities. Hence, the selection of a threshold value is crucial to generate the initial mask for brain tissues. The goal of achieving binarization of input image is to locate the region of membrane at brain surface and thus approximate the threshold value. This membrane identification includes removal of the background pixels from the input brain MR image and calculation of mean intensity value within this identified region. Based on the initial mean value of the entire image, the skull starting locations are approximated and final mean value is calculated for this identified region, which contains less number of background pixels.

The membrane of the brain is localized as the region, where the intensity, staring from initially approximated skull boundary, attains below the final mean value to the immediate exterior intensity of where intensity value, moving inwards, reaches above the final mean value. After identifying the membrane roughly, the threshold value is computed from the intensity values of pixels located withing the membrane region.

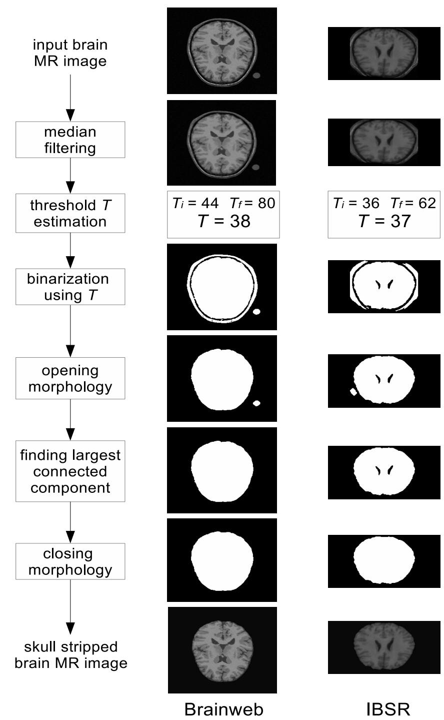


Fig. 1. Block diagram of the proposed method

If the slices of a brain MR volume have discontinuity along cerebral border line due to partial volume effects at skull boundary, the thresholding method cannot separate the brain region from the non-brain area. Hence, opening morphology filtering is applied to completely disjoint the brain and non-brain regions. Then, the brain portion is extracted as the largest connected component. There might be some holes within and along the periphery of the brain surface since the intensity values of CSF may be lower than the computed threshold value in some brain MR slices. Hence, closing morphology operation is embedded in the proposed methodology to produce the smoothed border and accurate skull-stripped brain MR images. Both of these morphology operations use an octagonal shaped structuring elements with different dimensions. The proposed methodology uses median filtering as denoising step prior to the calculation of threshold value as well as the application of morphological operations. Each of these steps of the proposed skull stripping methodology is enumerated below:

1) Apply median filtering with a window of size 3×3 to the input image.
2) Compute the initial mean intensity value T_i of the image.
3) Identify the *top*, *bottom*, *left*, and *right* pixel locations, from where brain skull starts in the image, considering gray values of the skull are greater than T_i.
4) Form a rectangle using the *top*, *bottom*, *left*, and *right* pixel locations.
5) Compute the final mean value T_f of the brain using the pixels located within the rectangle.
6) Approximate the region of brain membrane or meninges that envelop the brain, based on the assumption that the intensity of skull is more than T_f and that of membrane is less than T_f.
7) Set the average intensity value of membrane as the threshold value T.
8) Convert the given input image into binary image using the threshold T.
9) Apply a 13×13 opening morphological operation to the binary image in order to separate the skull from the brain completely.
10) Find the largest connected component and consider it as brain.
11) Finally, apply a 21×21 closing morphological operation to fill the gaps within and along the periphery of the intracranial region.

A graphical representation of the proposed skull stripping methodology is shown in Fig 1 for both synthetic (BrainWeb) and real (IBSR) brain MR images.

III. Experimental Results and Discussions

This section presents the qualitative and quantitative performance analysis of the proposed skull stripping method S3 on 37 T1-weighted brain MR volumes, along with a comparison with related skull stripping methods. The methods compared are BET, BSE, and ROBEX as described below:

- BET (version 2.1) [6]: brain extraction tool provided by FMRIB Software Library (FSL) (version 4.1.8) executed with default fractional intensity threshold value 0.5;
- BSE (version 13a4) [9]: brain surface extractor provided by BrainSuit executed using the default parameters: diffusion iterations = 3, diffusion constant = 25, edge constant = 0.64, erosion size = 1, trim spinal cord/brain stem = true, dilate final mask = true; and
- ROBEX (version 1.2) [11]: robust brain extraction maintained by Neuroimaging Informatics Tools and Resources Clearinghouse (NITRC).

The method S3 is implemented in C language and run in LINUX environment having machine configuration Intel(R) Core(TM) i7-2600 CPU @3.40GHz×8 and 16 GB RAM. To analyze the performance of different algorithms, the experimentation is done on some benchmark simulated MR images obtained from "BrainWeb: Simulated Brain Database" (www.bic.mni.mcgill.ca/brainweb/) and real MR images of "IBSR: Internet Brain Segmentation Repository" (www.cma.mgh.harvard.edu/ibsr/). All the image volumes of BrainWeb and IBSR are of size $256 \times 256 \times 181$ and $256 \times 128 \times 256$, respectively. In this regard, it should be noted that all the experiments are performed with no a priori knowledge about the input image. For a quantitative comparison of the performance of S3 with other skull stripping methods, the ground truth of brain matter, extracted from T1-weighted brain MR datasets of BrainWeb and IBSR available at their corresponding websites, are used. The comparative performance analysis is studied with respect to various segmentation metrics, namely, Jaccard index, Dice coefficient, sensitivity, and specificity.

Based on the region of interest to be segmented in the ground truth or reference image and segmented image, the false positive (FP), false negative (FN), true positive (TP), and true negative (TN) counts can be computed for each segmented image. The quantitative measures, namely, Jaccard index, Dice coefficient, sensitivity, and specificity, are described as follows with the help of these counts:

- The Jaccard similarity index measures the overlap between the ground truth and the result. It is defined as:
$$J = \frac{\mathrm{TP}}{\mathrm{FP} + \mathrm{TP} + \mathrm{FN}}. \tag{1}$$
- The Dice coefficient also measures set agreement, expressed as:
$$D(A, B) = \frac{2.\mathrm{TP}}{(\mathrm{FP} + \mathrm{TP}) + (\mathrm{FN} + \mathrm{TP})}. \tag{2}$$
- The sensitivity measures the fraction of true positives that are included in a segmentation, and is as follows:
$$SN = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}. \tag{3}$$
- The specificity measures the fraction of pixels, that do not belong to the region of interest, correctly detected, as determined by the equation:
$$SP = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}}. \tag{4}$$

Higher numbers in these metrics represent better overlapping in segmented image and ground truth image, indicating the significance of underlying algorithm. But, the sensitivity does not indicate whether the region of interest in segmented result includes more than the corresponding ground truth region and the specificity does not take into account whether or not the region of interest are labelled correctly. Thus these two measures are not used separately to measure the segmentation quality. The metrics are calculated here for brain tissues that include white matter, gray matter, CSF, and vessels.

In order to establish the performance of S3 over other popular existing methods, a large number of images, the slices selected randomly from BrainWeb subjects and IBSR volumes, are experimented. Fig. 2 and 3 present a few of them qualitatively obtained using different methods, along with the original images of BrainWeb and IBSR data sets, respectively,

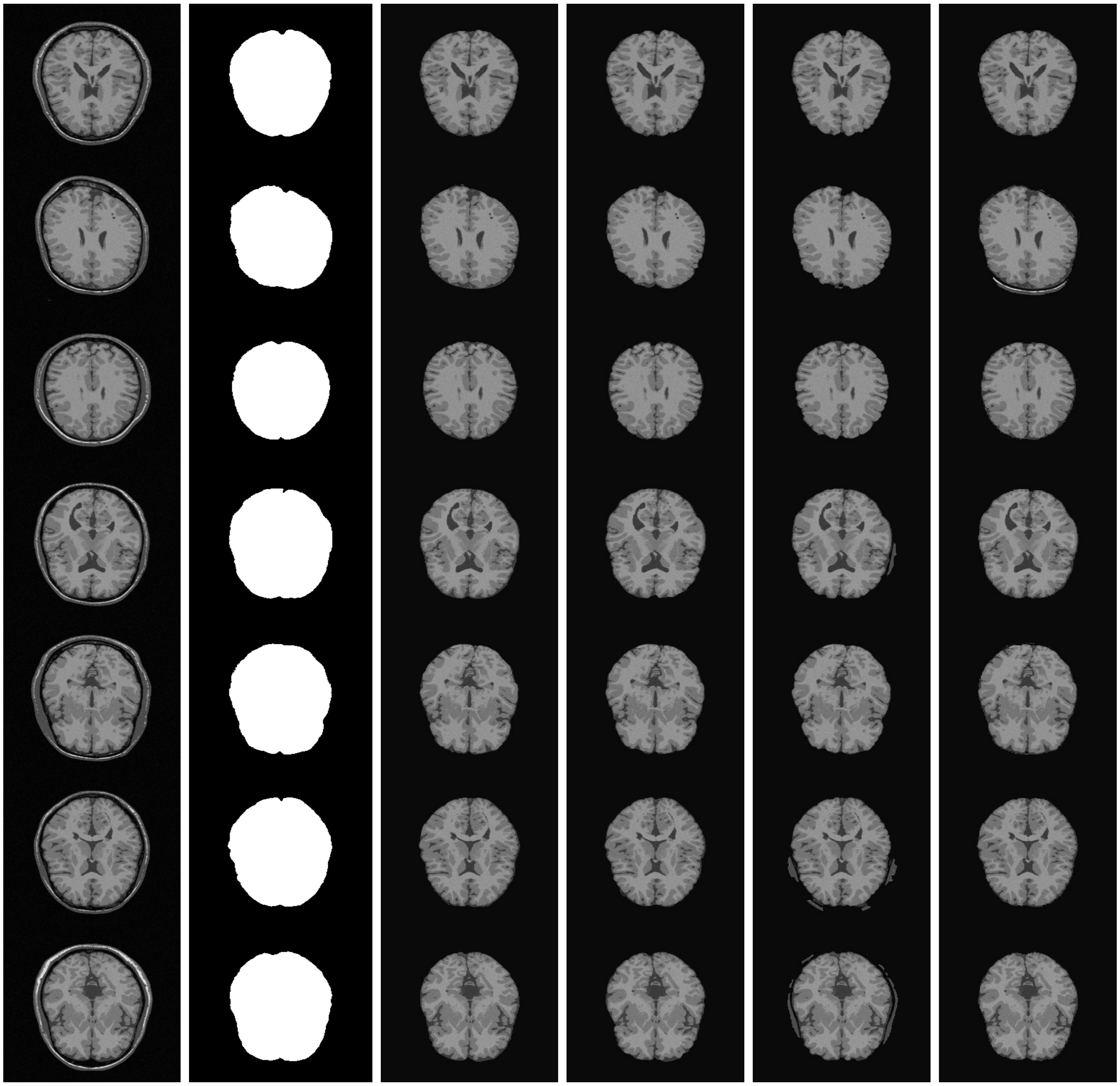
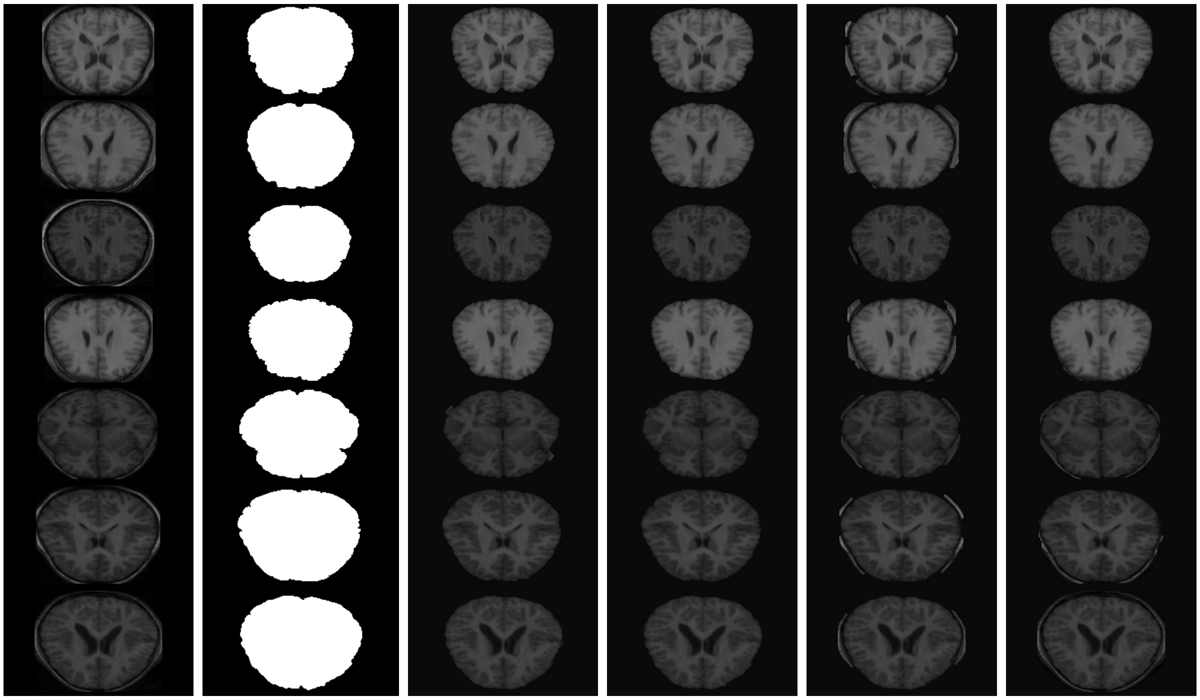


Fig. 2. Original, ground truth, and skull stripped images obtained using different methods on subject no. 4, 43, 44, 45, 47, 51, and 54 of BrainWeb

while Fig. 4 reports the effectiveness of the method S3 for more number of brain MR images quantitatively. The first, second, and third columns of Fig. 2 and 3 show the original images, corresponding ground truth images, and output skull stripped images obtained using S3, respectively, while remaining columns present the skull stripped images produced by different existing methods. The results in Fig. 2 and 3 show that over-extraction is done by BET in slices of BrainWeb subjects numbered 4, 43, and 44 by removing some brain tissues along the cerebral border. Under segmentation is experienced by BSE in slices of BrainWeb subjects numbered 45, 51, and 54, and it fails to remove the skull for most of the slices selected from IBSR dataset as shown in Fig. 3. That means, BSE works extremely poor on low contrast images like IBSR. The ROBEX also results in under segmentation in slices of BrainWeb subject numbered 43 and in slices of IBSR volumes numbered 5, 15, 16, and 17.

From the results reported in Fig. 4, it can be seen that the proposed skull stripping algorithm performs significantly better than BET, BSE, and ROBEX for segmenting the brain matter. Out of 37 cases, the performance of the proposed method S3 is better than that of BET in 29, 29, 21, and 30 cases with respect to Jaccard index, Dice coefficient, sensitivity, and specificity, respectively, while S3 attains higher performance compared to BSE in 33, 33, 19, 29 cases, respectively, and also to ROBEX in 32, 32, 9, 36 cases, respectively, irrespective of the data sets used. Hence, the best and consistent performance, irrespective of image contrast, is attained by the proposed method. However, the sensitivity value of the proposed method is lesser as compared to that of ROBEX in most of the cases. Since S3 adds some boundary portion of the CSF from brain region into its background, the false negative count is increased for the brain. So, out of total 37 cases, the proposed method attains higher sensitivity values in only nine cases compared



(i) Input (ii) Ground truth (iii) S3 (iv) BET (v) BSE (vi) ROBEX

Fig. 3. Original, ground truth, and skull stripped images obtained using different methods on volume no. 1, 2, 3, 5, 15, 16, and 17 of IBSR

to that of ROBEX. Hence, S3 performs better than BET, BSE, and ROBEX in 109, 114, and 109 cases, respectively, out of total 148 cases, irrespective of the quantitative indices and data sets used.

IV. Conclusion

The contribution of the paper lies in developing a methodology for removing skull from T1-weighted brain MR images as accurately as possible. This method is purely intensity based method, which include adaptive threshold calculation followed by morphological operations, for increased robustness. The sizes of octagonal structuring elements for opening and closing morphological operations are set experimentally. This method can be more robust by selecting the optimum values of morphology opening and closing sizes based on image characteristics. The proposed method does not require any user intervention or setting any external initial parameters to extract the brain matter and thus qualify to be an automatic method. Some existing methods such as BET [6] and BSE [9] also require parameter adjustment to obtain satisfactory results for different data sets used. Experimental results ensure that the proposed S3 method is suitable on both synthetic as well as real images, although they are low contrast images. It works well even for the brain volumes where BET [6], BSE [9], and ROBEX [11] fail to segment brain and non-brain regions accurately. This method is based on brain anatomy and image intensity characteristics and hence can be implemented as a part of any automatic brain image processing system [13].

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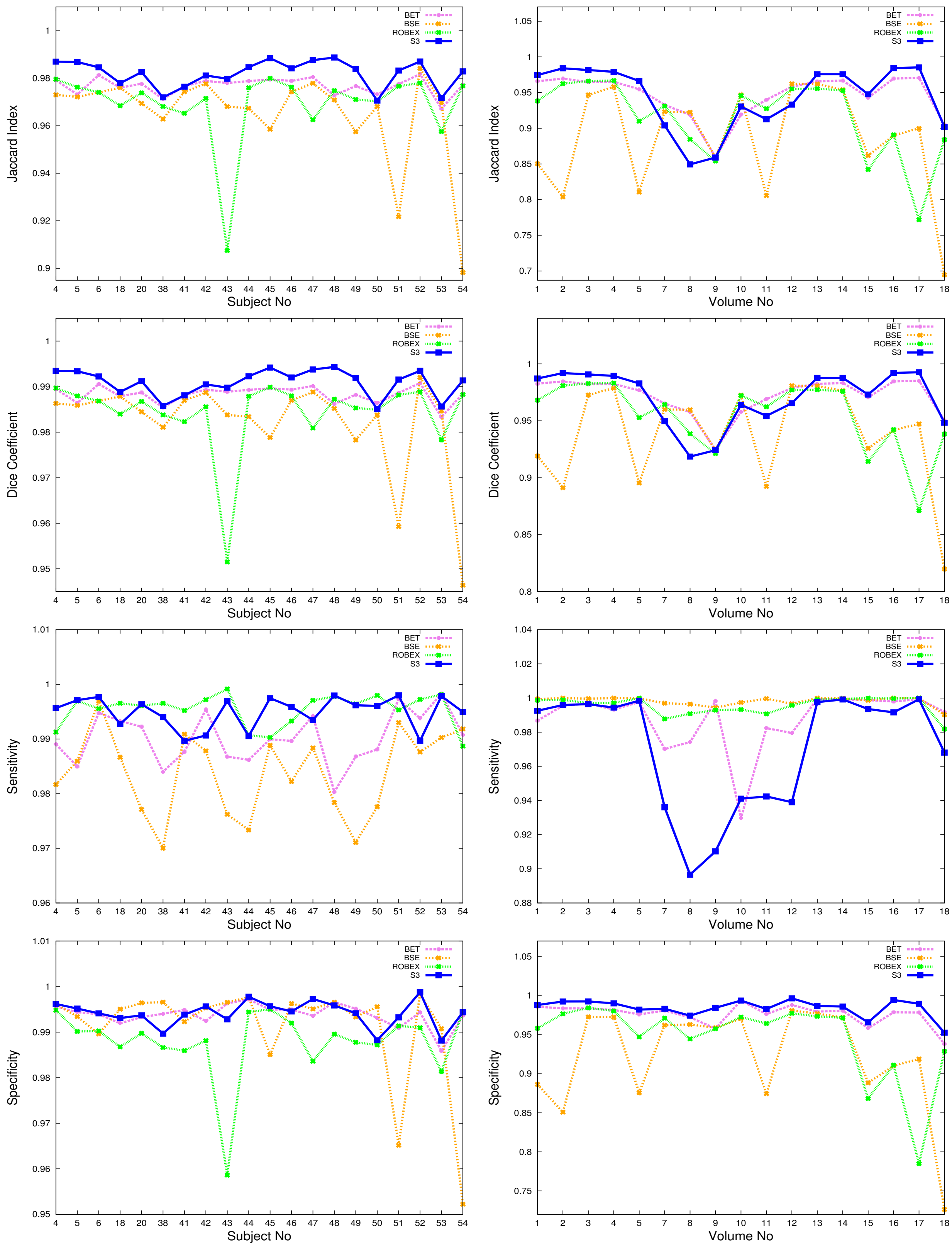

(i) BrainWeb (ii) IBSR

Fig. 4. Comparative performance analysis of the proposed method S3, BET, BSE, and ROBEX

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