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NEW BRAIN EXTRACTION METHOD USING EXPECTATION MAXIMIZATION AND MATHEMATICAL MORPHOLOGY

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ABSTRACT

The hi-tech development has led great success in both scientific and technical fields. Therefore we can obviously note that data processing takes less execution time and a smaller amount of human efforts. This is the advantage of the automatic line of work which aimed to reduce either physical or intellectual human effort. Furthermore it focused to let the painful and complex tasks to the machine including the computer.

In our framework, the processing of medical images (brain MRI) is transferred to the computer so the setting up of processing algorithms becomes an axis of rich researches highly open to discussion and development in our work, and we know that MRI is an effective examination of disease diagnosis, In this paper, we present our own method of brain extraction inspired by different methods in the literature namely brain method (BET; BSE, MSPL; MCSTRIP; TMBE ...) and different segmentation algorithms. Then, we compare our own way to other methods with excellent results using supervised evaluation criteria both outline and region.

Keywords : *Medical Image Processing; Segmentation; Supervised Evaluation; Brain Extraction; BET; BSE; MSPL; MCSTRIP; TMBE, EMBE.*

1. INTRODUCTION

No method was more effective with more accurate results than MRI (Magnetic Resonance Imaging) for diagnostics of diseases; this is why the study of MRI is very important, that's why most researchers have focused in this axis.

Brain extraction is the second step after the filtering of MRI should be applied, it can be defined as the elimination of all that is not brain in the MRI image (hair, skin, eyes ...), and so we must remove all non-brain subjects.

After the extraction of brain we can switch to the classification of different brain tissues (CSF, WM, GM), or downright segmentation of different brain parts useful for identified needs.

In general, a brain after extraction includes gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF). Brain extraction is accurate and crucial step such badly-suppressed brain tissue cannot be recouped in the subsequent processing steps, and failure to remove non-brain tissue could lead to false results during the analysis of MRI. To cope with all this; a number of brain automatic extraction methods have been developed.

Currently there are only three ways to make extraction of brain:

- Manual
- Thresholding with morphology
- Surface based model.

If we look for the good accuracy with more correct results it is best suited manual removal of the brain, but of course, there are enough major problems with manual segmentation to prevent it from being the best way to go. The first is the processing time which usually takes between 15 minutes and 2 hours. The seconds is the expertise and care during segmentation. For example, a clinical researcher who is not explicitly qualified will be likely to make a mistake in the differentiation between tissues such as the cerebellum and lower neighboring veins. That is why everyone prefers to spend automatic methods.

Thresholding morphology is semi-automatic method, A baseline segmentation foreground / background is achieved by using a simple threshold

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intensity, the user must be present and must help to choose threshold, it requires both the presence and the effort to choose the right threshold, and consequently it will ask more time, it would be difficult to cope with the huge MRI sequences.

The last way namely deformable surface models are relatively easier to automate the thresholding and morphology and more robust so it is the ideal of brain extractor, it uses deformable surface model; for example BET [1], Here, a surface model is defined, for example, checkered lattice triangles. This model is then "up" to the brain surface in the image. Normally, there are two main obstacles to development apart that imposes a certain form of softness onto the surface (both to maintain the well conditioned surface to correspond to the physical smoothness of the surface of the real brain) and part which fits the model in the correct part of the image in this case, the surface of the brain .The connection is usually achieved by deforming iteratively the surface of its starting position until an optimal solution is found.

Returning to our case, to set our brain extraction algorithm, we are often asked to create a mask of the brain. Actually this is the most difficult step that requires many studies and analysis. The step which comes after the creation of the mask will only be a logical function initiated (AND) with the primary image (MRI of the patient) and the mask created. We should present different methods of creating masks for the most commonly used algorithms (BTE, BSE; MCSTRIP; SMPE; TMBE) before presenting our method of creating the mask.

In fact to create our mask we are inspired by the segmentation algorithm Estimation Maximization (EM); known with its strong point of estimation and maximization. This algorithm is designed to fill in the missing data and it has very good results.

Our method creates the mask without thresholding which brings much good thing compared to thresholding methods and brings more precision in case the selected threshold may not be adequate or proper to give good results, so already our method will provide much more precision compared to the majority of previously proposed methods.

This work was necessary to help the doctors at diagnosis of diseases (Tumors, Alzheimer's ...), this may save a lot of time to specialists and physical and mental efforts during treatment of the large volume of MRI patients

Many brain extraction algorithms have been developed, so to prove the effectiveness of our method and show the positive contribution that our method will bring to the brain extraction, we must compare between our own method EMBE and five other famous most used methods of brain extraction, the first one will be BSE (Brain Surface Extractor); the second will be BET (Bain Extraction Tool); the third method is SPM2 (Statistical Parametric Mapping v2), the fourth will be McStrip (Minneapolis Consensus Strip) and the last is TMBE (Threshold Morphologic Brain Extraction).

First and foremost to introduce our own method we start with the presentation of fives methods that we used to compare and evaluate our proposed method.

2. METHOD DETAIL

In this section, we introduce the principles of methods that we will compare with our method namely EMBE, we are going to begin with BET:

2.1. BET (Brain Extraction Tool):

BET [1] is a robust automatic method of brain extraction, it is accurate and requires little time of simulation; they require no pre-processing before being used.

2.1.1. Estimation of threshold of intensity and Brain Parameters

The first step is the estimation of a few simple image parameters, so they look for the minimal and maximal intensity of the image ignoring the small numbers of pixels which have widely different values from the rest of the image;

2.1.2. Initialisation of Surface Model

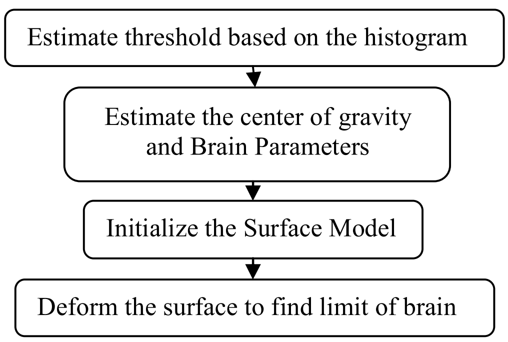
The brain surface is modeled by a surface composed of 4 small connected triangles; each vertex has neighbors.

2.1.3. Exterior Skull Surface Estimation

In this step; it deforms the surface to find the outline of the brain

We must consider that:

- The threshold of intensity was 0.2
- The threshold of gradient was 0.5



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2.2. BSE (Brain Surface Extractor)

BSE [2] is a powerful method, it has performed well on a large number of images and has been in public release for a few years; it was developed by a group of research in neuroimaging; this method finds anatomical boundaries that separate the brain from no brain subject.

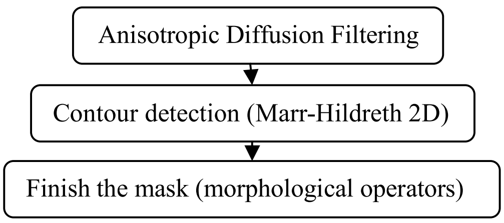
Based on the contour detection, she uses in the first step a filtering centered on the anisotropic diffusion because when we have low signal-to-noise ratios in the MRI, these boundaries will be obscured by noise and the edges will be indistinguishable from other edges.

The BSE uses a contour detection a Marr-Hildreth 2D operator; this detector produces closed contours and low execution time.

At the last step, she finishes the mask with morphological operators.

We give:

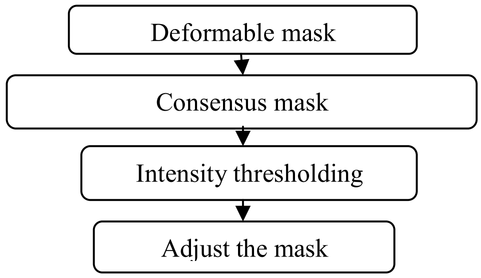
- The diffusion constant is 5
- The size of the core of contour detector is 0.98



2.3. McStrip (Minneapolis Consensus Stripping)

McStrip [3] [4] is an automatic method, it requires no user intervention, it use a masks created by different models to make a consensus mask. We can download the McStrip method in www.neurovia.umn.edu/incweb/McStrip_download.html.

So at the first step they start with the deformable mask AIR (Automated Image Registration) in general we can also find it in “http://bishopw.loni.ucla.edu/AIR5/”, after they dilate the mask to create a consensus mask, and they estimate the threshold between brain and non brain based on Intensity thresholding; after they automatically neaten this mask to produce a mask threshold.



2.4. SPM2 (Statistical Parametric Mapping V.2)

In the SMP2 method [14] we create the mask by the binary sum of the gray matter and the white matter of the brain after the segmentation.

To transform in the Talaraich space the step of realignment and normalization must be done; and to separate the gray matter of the white matter and the LCR we can use any simple methods of segmentation.

2.5. TMBE (Threshold Morphologic Brain Extraction)

This method is presented in 2011 by B.Cherradi and all [5], to simplify the complexity met in the other methods BET; BSE; McStrip; and SPM2, we can say that the strong point of this method is the simplicity and easiness.

She is divided into five stages:

2.5.1. Convert the MRI in binary image by optimal threshold

Based on global optimal threshold of MRI, we use here the method of Otsu [7]

2.5.2. Extraction of the biggest related component:

This step consists in extracting the region with the big surface; they use a statistical analysis of the related components.

2.5.3. Fill the holes:

The image gotten of the previous step (extraction of the biggest related component) present in general many holes, in this step they fill them.

2.5.4. Dilation

The objective here is to eliminate all small black stains remaining on the white component of the image gotten of the previous step, and to soften the outside borders of this component.

2.5.5. Brain Extraction

It is the last stage that permits the brain extraction; it will make itself while applying the operator "and" between the original image and the mask gotten in the stage "dilation"

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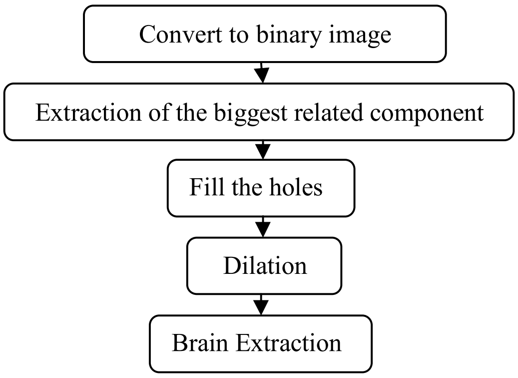
We summarizing:



Next we are going to present our method Expectation Maximization Brain Extractor (EMBE) that we will be compared after by the five other methods.

3. OUR METHOD (EMBE)

An overview of the different methods mentioned above in our article [15] has shown the complexity and the number of parameters to be optimized, which prompted us to develop a new method based on the benefits of some methods specially Expectation Maximization (EM) known by its point very strong (missing data, which will be very useful for filling holes when creating the mask brain).

The goal of our approach is to extract the brain of the brain image acquired: this will allow us to simplify the classification or segmentation of brain tissues (CSF, WM, GM). The region of interest is the brain. To extract the brain, we use the AND operator between the original image and the binary mask obtained by the EM algorithm. Non-brain tissues are obtained by applying the AND operator between the original image and the logical complement of the mask created. Our method is simple, highly efficient and requires very little time before the execution of most of the methods presented earlier, it can be divided into four steps as follows:

3.1. Creation Of The Mask Using The EM Algorithm:

The expectation maximization algorithm was originally described in its general form by Dempster [16] it has been widely applied to estimate the hyper-parameters in statistical segmentation of MRI images. It is often used in evaluation problems where some missing data.

Principle is illustrated as follows: it alternates evaluation expectancy (E) steps, here it calculates the expectation of the likelihood taking account the recent observed variables; and a maximization step (M); Here he estimates the maximum likelihood of the parameters by maximizing the likelihood found in step (E); it still uses the settings found in M as the starting point of a new phase of evaluation expectancy, and finally as it iterates phases E and M.

The objective of the EM is then: find the maximum likelihood parameters of probabilistic models when the model depends on unobserved latent variables.

We recall that the goal is to complete a series of missing data based on the maximum likelihood.

We give here the steps E and M [17]:

1- the step of the expectation (E):

Evaluation expectancy (1) according to the observed data and the parameters available to us
Is sought to determine the parameter Θ:

$$Q\left(\theta;\theta^{(c)}\right) = E\left[\,L\left((x);\theta\right)\right|\theta^{(c)}] \qquad (1)$$

With: log-likelihood is

$$L(x;\theta) = \sum_{i=1}^{n} log f(x_i\ ,\theta) \qquad (2)$$

2- the step of the maximization (M):

Maximizing this expectancy (3):

$$\theta^{(c+1)} = \arg\max(Q\left(\theta,\theta^{(c)}\right)) \qquad (3)$$

EM algorithm is defined as follows:

- Initialization randomly
- c = 0
- As long as the algorithm has not converged do
  Evaluation of the expectation (E step):
  $Q\left(\theta;\theta^{(c)}\right) = E\left[\,L\left((x);\theta\right)\right|\theta^{(c)}$
- Maximization (M-step):
  $\theta^{(c+1)} = \arg\max(Q\left(\theta,\theta^{(c)}\right))$
- c = c + 1
- end

By applying the EM algorithm is obtained brain mask directly, which saves us two steps in comparison with the method TMBE (which are thresholding and filling holes), the latter step (filling holes) that is made entirely by the EM algorithm and of aillor remind us that this is the strong point of the EM method (estimating missing data that will be for us black holes left on the mask white brain by thresholding in the TMBE case).

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Therefore the algorithm will provide an effective mask EM and no need of adjustment and filling holes.

3.2. Extraction Of The Largest Connected Component (Brain Mask):

Based on the result of step 'creation of the mask with the EM algorithm', we will need in the second step (which is the extraction of the largest connected component brain mask), so to achieve this we have uses statistical analysis of existing connected components in the image result of EM. Figure1-b, Figure1-c, Figure2-b and Figure2-c show the result of this operation.

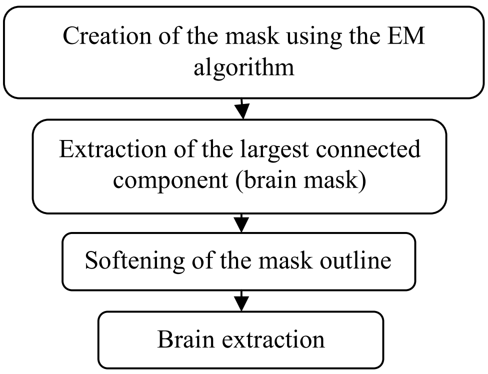
3.3. Dilatation (Softening Of The Mask Outline):

After obtaining the mask with the expectation maximization algorithm, we need to soften the exterior boundaries of the component, for this we made use of mathematical morphology, the principle here is the expansion of adjacent white areas so we moved a circular structuring element surface ($\pi * r^2$) on the resulting image, and applying a logical or (sum) on each of the (($\pi * r^2$) -1) neighboring pixels An empirical study and assigning different values to r; we went out with r = 1.5 as the radius that gives the best result of the brain mask.

3.4. Brain Extraction:

Finally to extract our region of interest and that is the brain, we use the operator "and" between the original image and the final mask obtained in the previous step as shown in Figure1-e and Figure2-e.

If you want to have non-brain tissue we apply the operator "and" between the source image and the complement of the final mask.



We present the results of these steps applied to two cerebral MRI. The result of our method applied on a real MRI image offered in brain web database.

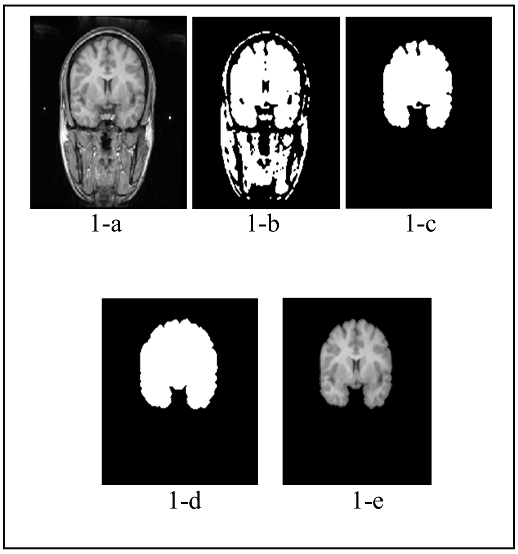


Figure 1: A- Original MRI Image; B- EM Brain Mask; C- Extraction Of The Largest Component; D- Dilatation; E- Brain Extraction.

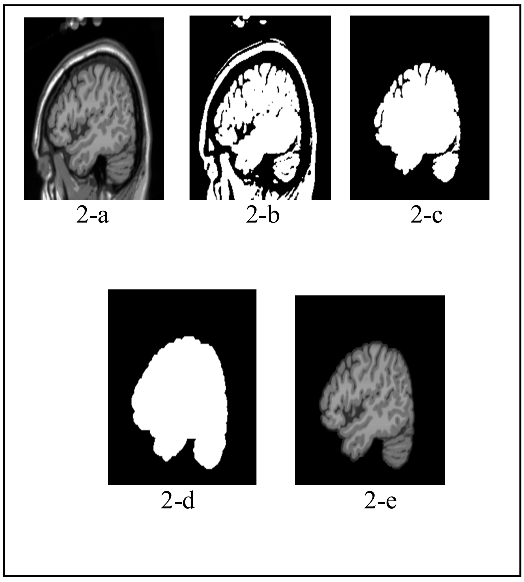


Figure 2: A- Original MRI Image; B- EM Brain Mask; C- Extraction Of The Largest Component; D- Dilatation; E- Brain Extraction.

4. CRITERIA FOR EVALUATION

Now after the presentation of our proposed method and the other five methods with which we

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will compare our method, the next step will be the presentation of the various criteria of evaluation in order to evaluate and compare methods

To compare the performance of our method (EMBE) proposed in this article, we should calculate different coefficients that will reflect the way in which two regions are segmented, namely: Those regions are automatically segmented by these six studied techniques and so on with the regions which are manually segmented and used here like reference images;

Among the measures of performances the most used in literature to establish a comparison between the brain extraction methods, we will use in the following:

- Time;
- Jaccard's similarity coefficient;
- Dice's similarity coefficient;
- Sensitivity;
- Specificity;

4.1. Jaccard:

This similarity coefficient of Jaccard "Jsc" [9] is calculated as follows:

$$Jsc = Card\ (R_1 \cap R_2) / Card\ (R_1 \cup R_2)$$

We define:

R_1: The region segmented automatically.
R_2: The region of the image segmented manually
Card (x): Indicates the number of pixels in region x

For evaluation will lead us to normalize the results between 0 and 1. So that if Jsc value is near 1, the result is perfect (this is what we search). If the value is near 0, we conclude that the result bad and it is far from what is to be desired.

4.2. Dice:

The Dice similarity coefficient [10] is used to evaluate the degree of similarity; from an automatically segmented region by two different methods; or between two regions in which one is automatically segmented and the other manually segmented (reference) as in our case.

Dice coefficient is calculated by:

$$DSC = 2^*\ Card\ (R_1 \cap R_2) / Card\ (R_1 + R_2).$$

Where:

R_1: The region segmented automatically.
R_2: The region of the image segmented manually
Card (x): Indicates the number of pixels in region x

The Dice similarity is the same like the Jaccard similarity. So like the evaluation criteria of Jaccard, we have normalized the results between [0, 1] where 1 corresponds to a perfect result (desired) and 0 corresponds to a bad result (unwanted).

4.3. Similarity:

We will calculate the sensitivity coefficient from the results of the six methods discussed in this article by using the mask of the image manually segmented.

The sensitivity is the percentage of pixels recognized by the algorithm.

It is given by the next equation:

$$Sens. = \frac{TP}{TP + FN}$$

Where:

TP: True positives: The pixels number from R1 is correctly classified like R2.
FN: False negatives: The pixels number from R1 is incorrectly unclassified as R2.
R1: MRI segmented automatically.
R2: MRI segmented manually.

4.4. Specificity

Specificity is the percentage of pixels not recognized by the algorithm. It is given by the next equation:

$$Spec. = \frac{TN}{TN + FP}$$

Where:

TN: True negatives: The pixels number from R1 is correctly unclassified as R2.
FP: False positives: The pixels number from R1 is incorrectly classified as R2.
R1: MRI segmented automatically.

R2: MRI segmented manually.

5. RESULTS & DISCUSSION

5.1. Implementation:

We mention that the implementation of the six programs was made by using the scientific programming language "MATLAB 7.8" that generates a file extension (.m) and we have executed it on a personal computer processor Intel

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Core i3 of frequency 2.3 GHz with 4GB principal memory and a graphics card Intel HD 3000.

5.2. Results:

With the purpose of comparing and proving the effectiveness of our method, we have applied these methods namely: (BET, BSE, McStrip, TMBE, SPM2, and EMBE) on real and simulated MRI images.
These MRI images are listed as follows:

- 20 weighted simulated volumes T1 sized (181 x 217 x 181 pixel) were recovered from database Brain Web [A]. I note that their manual segmentation is also available with images. Their spatial resolutions are (1m x 1m x 1m) sized by pixels dimensions ;

- 18 weighted real volumes T1 sized (256 x 256 x 128 pixel) were recovered from the database of MRI and manual segmentation of experts: internet brain segmentation repository IBSR V2.0 [www.cma.mgh.harvard.edu/ibsr/] of Massachusetts Morphomertry Analysis General Hospital Center. All data MRI of the brain and their manual segmentations in three tissues is provided by the experts radiologists from that Center;

In the next table [Table1] we present our different results; to evaluate we calculate different criteria of evaluation for different brain extraction techniques applied on MRI cerebrals images T1 (181x217x181) from Brain web database.

*Table1: Results for T1-weighted MRI volume 181*217*181 from Brainweb dataset*

methods	JSC	DSC	Sens.	Spec.	time
BET	0.81	0.76	0.603	0.912	3min
BSE	0.82	0.88	0.607	0.973	2min
McStrip	0.80	0.84	0.600	0.903	6min
SPM2	0.81	0.87	0.604	0.902	4min
TMBE	0.80	0.87	0.599	0.901	4min
EMBE	0.81	0.89	0.600	0.930	3min

In the following table [Table2] we present the different results; using different criteria of evaluation, it was calculate for different brain extraction techniques applied on MRI cerebrals images T1 (256x256x256) from IBSR V20.

*Table2 : Results for T1-weighted MRI volume 256*256*256 from IBSR V.2 dataset*

methods	JSC	DSC	Sens.	Spec.	time
BET	0.85	0.78	0.600	0.902	3min
BSE	0.86	0.89	0.622	0.923	2min
McStrip	0.82	0.82	0.610	0.913	6min
SPM2	0.84	0.85	0.600	0.910	4min
TMBE	0.84	0.86	0.591	0.923	4min
EMBE	0.85	0.89	0.610	0.914	3min

5.3. Discussion:

We present the results of experiments applied on MRI images in the Table 1 and Table 2. Our method is efficient as a whole; the algorithm was able to determine accurately the outline of the brain and in a shorter time in comparison with the majority of the proposed methods (except for BSE). In addition, our method proved more robust than others (TMBE, BET, McStrip, and SMP2), as seen in both tables, the BSE also offers very robust results. We recall that we have evaluated the performance of our algorithm tested on simulated and real MRI images.

Our method uses the robustness of the expectation maximization (EM) algorithm, subsequently there is no doubt of its robustness, it also has 4 easy steps to get the desired result in comparison with other methods can be widely see the simplicity of our method which directly reflects on the simplicity of the establishment of the program for the simulation.

According to the comparative tables we can see that the fastest method is BSE (2 min) followed by followed by our method EMBE (3 min), but we can see that Mc Strip method is the slowest with (6 min).
So if there is a huge volume of images to examine and we are limited by time we must choose between our method or BSE method.

We note that we normalize the results between the value 0 and the value 1, so any value close to 1 indicates a good result, while the result close to 0 reveals an undesirable result.

Now we evaluate the accuracy: the BSE method prevails for the reason that its results are close to the value "1" followed once more again by our method and in third position comes the TMBE method while Mc strip's method ranks last for its lack of precision.

So if we want to save time and have accurate results or relatively correct, BSE method or our method is advised.

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And if we evaluate the implementation of the program and even the establishment of the program and its completion, we can say in this case that our method is the most conclusive since it uses only EM algorithm and mathematical morphology (AND) as described in paragraph (III).

So according to the simplicity criteria and the program's complexity, the use of our method is mostly advised.

6. CONCLUSION

The extraction of the brain, also known under "pickling the skull" or intracranial segmentation, seeks to eliminate non-brain tissues, such as: skull, leather, hairy ... and retaining only brain in the image to be processed. It has become a standard procedure in preprocessor brain MRI images, which is crucial for image analysis.

In this article we have presented our brain extraction algorithm namely EMBE (Expectation Maximization Brain Extractor), based on the robustness of the algorithm used by its expectation maximization strong point maximizing Esperance of likelihood from data already observed in the image, this algorithm has proven several times its accuracy in the case of missing data, so in our method we used this strength, which resulted eventually to the robustness of our brain extraction method, after using the EM algorithm we directly will extract the largest connected component in the image that is the brain mask, and for a smoother mask, we introduced dilatation step that is aimed smooth the edges brain mask by moving along a circular area of the brain mask, and last phase we made the extraction of the brain by applying the logical 'AND' between the source image and the created mask.

And at the last step we compare between our method and five other methods of brain extraction, four methods the more used in the literature (BET; BSE; McStrip; SPM2), and a method lately presented TMBE, known by her simplicity.

We validated our method on phantom and real human data and demonstrated that our method gives a good result and that it outperformed several published methods.

The proposed method was evaluated on 20 weighted simulated volumes T1, and 18 weighted real volumes T1, achieving better performance than other methods such as BSE; McStrip, TMBE and SPM2.

WEB SERVICE

We have also used a Brain Extraction Evaluation Web Service available at http://www.neurovia.umn.edu. To use this service, we download a set of 15 anonymized T1- weighted MRI volumes, strip them by hand or with an in-house BEA, and upload the resultant strip masks to the service website.

The results of the comparison are automatically send by e-mail with comparable results for BSE; BET; McStrip, and SPM2.

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