A New Approach for Segmentation of Brain MR Image

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Abstract: In the frame of medical imaging, accurate segmentation of brain MR images is of interest for many brain disorders. However, due to several factors such noise, imaging artifacts, intrinsic tissue variation and partial volume effects, tissue segmentation remains a challenging task. So, in this paper, a full automatic framework for segmentation of brain MR images is presented. The framework consists of three-step segmentation procedure. First, segmentation of brain/non-brain tissue is performed by using Hybrid watershed algorithm (HWA). Then the intensity inhomogeneity correction method is applied to MR image. Finally, Fuzzy Kohonen's Competitive Learning (F-KCL) Algorithms are used for MRI tissue segmentation. The efficiency of the proposed framework is demonstrated by extensive segmentation experiments using simulated MR images.

Keywords: Magnetic resonance imaging, MRI segmentation, Skull stripping, Intensity in homogeneity correction.

1. Introduction

Magnetic resonance (MR) imaging has been widely applied in biological research and diagnostics, primarily because of its excellent soft tissue contrast, non-invasive character, high spatial resolution and easy slice selection at any orientation. In many applications, its segmentation plays an important role on the following sides: (a) identifying anatomical areas of interest for diagnosis, treatment, or surgery planning paradigms; (b) preprocessing for multimodality image registration; and (c) improved correlation of anatomical areas of interest with localized functional metrics [1].

Intracranial segmentation commonly referred to as skull-stripping, aims to segment the brain tissue (cortex and cerebellum) from the skull and non-brain intracranial tissues in magnetic resonance (MR) images of the brain. Skull-stripping is an important preprocessing step in neuroimaging analyses because brain images must typically be skull-stripped before other processing algorithms such as registration, tissue classification or bias field correction can be applied [2-6]. In practice, skull-stripping is widely used in neuroimaging analyses such as multi-modality image fusion and inter-subject image comparisons [2, 3]; examination of the progression of brain disorders such as Alzheimer’s Disease [7, 8], multiple sclerosis [9-12] and schizophrenia [13, 14]; monitoring the development or aging of the brain [15], [16]; and creating probabilistic atlases from large groups of subjects [2].

Numerous automated skull-stripping methods have been proposed [17], [18], [19], [20], [5], [21] are widely used. However, the performance of these methods, which rely on signal intensity and signal contrast, may be influenced by numerous factors including MR signal inhomogeneities, type of MR image set, gradient performance, stability of system electronics, and extent of neurodegeneration in the subjects studied [21].

Fully automatic brain tissue segmentation of magnetic resonance images (MRI) is of great importance for research and clinical study of much neurological pathology. The accurate segmentation of MR images into different tissue classes, especially gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF), is an important task. Moreover, regional volume calculations of these tissues may bring even more useful diagnostic information. Among them, the quantization of gray and white matter volumes may be of major interest in neurodegenerative disorders such as Alzheimer disease, in movements disorders such as Parkinson or Parkinson related syndrome, in white matter metabolic or inflammatory disease, in congenital brain malformations or perinatal brain damage, or in post traumatic syndrome. The automatic segmentation of brain MR images, however, remains a persistent problem. Automated and reliable tissue classification is further complicated by the overlap of MR intensities of different tissue classes and by the presence of a spatially smoothly varying intensity inhomogeneity.

Here a full automatic framework for brain MRI segmentation is presented. The system combines the HWA method [20] for non brain tissue removal, the bias field correction schema by Wells et al. [22], and Fuzzy Kohonen's Competitive Learning Algorithms for tissue segmentation. Extensive experiments using simulated MR image data show that the proposed method can produce good segmentation results.

The reminder of this paper is organized as follows. Section 2 presents the proposed segmentation framework. Simulation results are introduced in section 3. Finally conclusion is given in Section 4.

2. The Proposed Framework

The proposed full automatic framework for brain MR image segmentation consists of a sequence of processing
steps are shown in flow diagram form in Figure 1 and includes: (1) Input the MRI image data; (2) Removal of non-brain tissue (3) intensity inhomogeneity (IIH) correction; (4) Fuzzy Kohonen’s Competitive Learning Algorithms for brain tissue segmentation.

![Figure 1: The flow chart of the proposed framework of automatic MR image segmentation](image)

**A. Skull stripping process**

Segmentation of brain/non-brain tissue is one of the most time-consuming preprocessing steps performed in neuroimaging laboratories. As a result, numerous brain extraction algorithms (BEAs) have been developed to perform this step automatically. While BEAs speeds up overall image processing, their output varies greatly and can affect the results of subsequent image analysis.

Here we provide a quantitative comparison of the performance of four BEAs – Brain surface Extractor (BSE), Brain Extraction Tool (BET), hybrid Watershed Algorithm (HWA) and McStrip - against the “gold standard” of expert manual brain extraction using high-resolution T1-weighted MRI brain volumes.

**(1) Brain Surface Extractor (BSE):**

BSE is an edge-based method, uses a sequence of anisotropic diffusion filtering, Marr-Hildreth edge detection, and morphological processing to segment the brain within whole-head MRI. Briefly, BSE works in three steps: first, the image is smoothed to reduce noise using anisotropic diffusion filtering. Second, edge detection (Marr-Hildreth edge detector) is applied to the smoothed image. Finally, the edge image is further processed to identify the largest connected region and to smooth the surface of this region. The largest remaining connected region is assumed to represent the brain. An additional dilatation and erosion is performed to fill in surface pits and small holes [19], [5].

BSE v. 3.3 is freely available for download from http://neuroimage.usc.edu/brainsuite/, the BrainSuite website, the developers recommended the following parameters for automated processing of both legacy and contemporary image sets: anisotropic filter = 5 iterations with 5.0 diffusion constant; edge detector kernel = 0.8 sigma. These parameters were utilized in this study.

**(2) Brain Extraction Tool (BET):**

BET [21] employs a deformable model to fit the brain’s surface using a set of “locally adaptive model forces”. This method estimates the minimum and maximum intensity values for the brain image, a “centre of gravity” of the head image, and head size based on a spherical equivalent, and subsequently initializes the triangular tessellation of the sphere’s (head’s) surface.

BET v. 1.2 is freely available in the FMRIB FSL Software Library (http://www.fmrib.ox.ac.uk/fsl/). The developer recommended the default parameters for automated processing of both the legacy and contemporary images. The parameters utilized in the application herein are the default parameters, described as follows: fractional intensity threshold = 0.5; vertical gradient in fractional intensity threshold = 0.

**(3) Minneapolis Consensus Strip (McStrip):**

McStrip[23], [24] is an automatic hybrid approach to brain extraction from T1-weighted MR volumes that uses a hierarchy of masks created by different models to form a consensus mask. The algorithm (McStrip) incorporates atlas-based extraction via nonlinear warping, intensity-threshold masking with connectivity constraints, and edge-based masking with morphological operations.

McStrip is an automatic hybrid algorithm implemented in IDL that incorporates BSE and requires no user intervention; it relies on warping to a template, intensity thresholding, and edge detection.

**(4) Hybrid Watershed Algorithm - Version 1.21 (HWA):**

HWA [20] method is a hybrid of a watershed algorithm [18] and a deformable surface model [17] that was designed to be conservatively sensitive to the inclusion of brain tissue. In general, watershed algorithms segment images into connected components, using local optima of image intensity gradients. Deformable surface-model is then applied to locate the boundary of the brain in the image.

HWA v. 1.21 is freely available as a component of the FreeSurfer software package at http://surfer.nmr.mgh.harvard.edu/. HWA developers recommended the default parameters for automated processing of both legacy and contemporary images. The parameters utilized in this study are the hard-coded default parameters of HWA.

**Performance Measure:**

To compare the performance of various segmentation techniques, we compute different coefficients reflecting how well two segmented volumes match. The manually segmented brains are used as a gold standard, and the automatically extracted brains are compared to them.

To provide fair comparison between methods, we use a different performance measure:
1. Jaccard similarity coefficient [35]:

The Jaccard similarity coefficient $JSC$ is formulated as

$$JSC = \frac{\text{vol}(S \cap S_s)}{\text{vol}(S \cup S_s)}$$  \hspace{1cm} (1)$$

where $S_i$ is the automatically skull stripped region, $S_s$ is the brain region of the manually stripped image, and $\text{vol}(X)$ denotes the volume of the region $X$. A Jaccard similarity coefficient of 1.0 represents perfect overlap, whereas an index of 0.0 represents no overlap. JSC values of 1.0 are desired.

2. Dice Similarity Coefficient:

Dice Similarity Coefficient [36] is used to show the similarity level of automatically stripped region to manual stripped image.

The Dice coefficient is defined as

$$D = \frac{2\text{vol}(S \cap S_s)}{\text{vol}(S) + \text{vol}(S_s)} = \frac{2\text{JSC}}{1 + \text{JSC}}$$  \hspace{1cm} (2)$$

where $S_i$ is the automatically skull stripped region, $S_s$ is the brain region of the manually stripped image, and $\text{vol}(X)$ denotes the volume of the region $X$. A Dice similarity coefficient of 1.0 represents perfect overlap, whereas an index of 0.0 represents no overlap. D values of 1.0 are desired.

3. Sensitivity and Specificity [37]:

We also compute the sensitivity and specificity coefficient of the automated segmentation result using the manually segmented brain mask. The Sensitivity is the percentage of brain voxels recognized by the algorithm (Equation 3). The Specificity is the percentage of non-brain voxels recognized by the algorithm (Equation 4).

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$  \hspace{1cm} (3)$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$  \hspace{1cm} (4)$$

Where TP and FP stand for true positive and false positive, which were defined as the number of voxels correctly and incorrectly classified as brain tissue by the automated algorithm. TN and FN stand for true negative and false negative, which were defined as the number of voxels correctly and incorrectly classified as non-brain tissue by the automated algorithm.

4. Processing Time: The time necessary for generating the final brain mask for each Brain Extraction Algorithm was recorded.

The four Brain Extraction Algorithms (BEAs) are tested using two datasets of brain T1-weighted MR images and evaluated the result against manual skull-stripped image that used as a “gold standard”. Moreover, Figure 2 shows the brain mask that obtained from the four BEAs on the slice in datasets#1, and the “gold standard” brain mask. The brief definition of the evaluation methods and the average evaluation result are summarized in Table 1, Table 2.

![Figure 2: Original MRI, manual mask, BSE mask, BET mask, McStrip mask, and HWA mask.](image)

<table>
<thead>
<tr>
<th>Performance measure</th>
<th>JSC</th>
<th>Dice</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>time</th>
</tr>
</thead>
<tbody>
<tr>
<td>BET</td>
<td>0.79</td>
<td>0.76</td>
<td>0.90</td>
<td>0.902</td>
<td>10 sec</td>
</tr>
<tr>
<td>BSE</td>
<td>0.82</td>
<td>0.88</td>
<td>0.907</td>
<td>0.97</td>
<td>2 min</td>
</tr>
<tr>
<td>McStrip</td>
<td>0.93</td>
<td>0.95</td>
<td>0.94</td>
<td>0.98</td>
<td>6 min</td>
</tr>
<tr>
<td>HWA</td>
<td>0.96</td>
<td>0.98</td>
<td>0.97</td>
<td>0.99</td>
<td>4 min</td>
</tr>
</tbody>
</table>

Table 1: Dataset#2, BEA performance on repeat scans of a single object vs. manual mask

<table>
<thead>
<tr>
<th>Performance measure</th>
<th>JSC</th>
<th>Dice</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>time</th>
</tr>
</thead>
<tbody>
<tr>
<td>BET</td>
<td>0.80</td>
<td>0.75</td>
<td>0.903</td>
<td>0.90</td>
<td>15 sec</td>
</tr>
<tr>
<td>BSE</td>
<td>0.82</td>
<td>0.87</td>
<td>0.90</td>
<td>0.963</td>
<td>2.5 min</td>
</tr>
<tr>
<td>McStrip</td>
<td>0.93</td>
<td>0.94</td>
<td>0.94</td>
<td>0.97</td>
<td>6 min</td>
</tr>
<tr>
<td>HWA</td>
<td>0.95</td>
<td>0.98</td>
<td>0.973</td>
<td>0.987</td>
<td>3.67 min</td>
</tr>
</tbody>
</table>

Table 2: Dataset#2, BEA performance on repeat scans of a single object vs. manual mask

HWA algorithm performed best when compared to manual mask with regard to JSC, Dice, sensitivity and Specificity. But BET performed fastest; creating mask in less than 1 min.
The comparison of four BEAs techniques against expertly hand stripped T1-weighted MRI volumes revealed that HWA algorithm, a hybrid approach incorporating watershed algorithm and deformable model, outperformed BSE, BET, and McStrip, all of which rely on a single algorithmic strategy.

B. Intensity Inhomogeneity (IIH) correction:

Inhomogeneity in magnetic fields during image acquisition and magnetic susceptibility variations in scanned subjects cause intensity non-uniformities, also described as bias fields. These artifacts prevent characterization of voxel tissue content based solely on image intensity. As a result, segmentation as well as quantitative studies of MR images requires compensation for these non-uniformities. The method we implement is due to Wells [22].

Let \( Y \) be the observed image, \( X \) the ideal image, \( B \) the inhomogeneity, and \( N \) the noise present in the image. The interactions between these fields can be described as:

\[
Y = X \times B + N
\]

The noise is considered negligible. Taking the logarithm of Eq.5 gives:

\[
log(Y) = log(X) \times log(B)
\]

Assuming that the pixel intensities of a tissue type are normally distributed, the probability for a pixel to belong to a class, in absence of inhomogeneities, can be expressed as:

\[
p(y_i / x_i) = \frac{1}{\sqrt{2\pi\sigma_i}} \exp\left( -\frac{1}{2} \left( \frac{y_i - \mu_i}{\sigma_i} \right)^2 \right)
\]

\[
= G_{\sigma_i}(y_i - \mu_i)
\]

where \( y_i \) represents the intensity of image pixel, \( k \) number of a single class, \( \mu_i \) mean of class \( k \), \( \sigma_i \) represents the standard deviation of class \( k \).

In the presence of inhomogeneities, and according to Eq.6 and Eq.7, the same probability can be expressed as:

\[
p(y_i / x_i, \beta_i) = G_{\sigma_i}(x_i - \mu_i - \beta_i)
\]

where \( \beta_i \) is the inhomogeneity at this \( i_{th} \) pixel location. To estimate the inhomogeneity, the residual term \( R_i \) is computed for each pixel:

\[
R_i = \sum_k p(x_i / y_i) \frac{y_i - \mu_i}{\sigma_i}
\]

The inhomogeneity at the \( i_{th} \) pixel location, \( \beta_i \), is the average of the \( R_i \) in a \( 3 \times 3 \) neighborhood of pixel \( i \).

Figure 3 presents the results of the estimated bias field. The method consists two steps:

1. Estimation of the tissue type for all the pixel \( y_i \) of the image.
2. Estimation of the inhomogeneity \( \beta_i = \text{mean}(R_i) \) at each location \( i \) in the image, and correction according to Eq.6. The method is iterative, and is initialized with inhomogeneities equal to zero.

C. Segmentation:

The goal of brain magnetic resonance image segmentation is to accurately identify the principal tissue structures in these image volumes. There are many methods that exist to segment the brain. One of these, conventional methods that use pure image processing techniques are not preferred because they need human interaction for accurate and reliable segmentation. Unsupervised methods, on the other hand, do not require any human interference and can segment the brain with high precision. In the light to this fact, we compare here the performance of four image segmentation techniques in the subject of brain MR image. Results show that Fuzzy Kohonen’s Competitive Learning (F-KCL) Algorithms performs better in terms of segmentation accuracy, while Fuzzy C-Means (FCM) performs better in terms of speed of computation.

Methods

(1) The Self-organizing Feature Map algorithm (SOFM)

With the aim of obtaining adaptive image processing, researchers have tried to employ neural network (NN) approaches. Here, the basic objective is to emulate the human vision processing system which is highly robust and noise insensitive and hence can be applied even when information is ill defined and/or defective/partial. A self-organizing map (SOM) is a type of artificial neural network that is trained using unsupervised learning to produce a low-dimensional (typically two dimensional), discretized representation of the input space of the training samples, called a map. The map seeks to preserve the topological properties of the input space.

Every input is connected extensively to every output node via adjustable weights. Let \( X = [x_0, x_1, ..., x_n] \) be a set of
$N$ inputs in $\mathbb{R}^N$ such that each $x_i$ has $N$ dimensions (or features). Let $P$ be the number of output node and $W_j = [w_{ij}, w_{ij}, \ldots, w_{ij \cdot N}]$ denote the weights or reference vectors. $x_i$ denotes the input to output node $j$ and $w_{ij}$ is the weight from input node $i$ to the output node $j$. $W_j$ is the vector containing all of the weights from $N$ input nodes to output node $j$. Updating weights for any given inputs in SOFM form is only for output units in a localized neighborhood. The neighborhood is centered on the output node whose distance $d_j$ is minimum. The measurement of $d_j$ is an Euclidean distance, defined as:

$$d_j = \min_j \| x_i - w_{ij} \|^2 \quad (10)$$

The neighborhood decreases in size with time until only a single node is inside its bounds. A learning rate, $\sigma_j(t)$, is also required which decreases monotonically in time. The weight updating rule is as follows:

$$w_{ij}(t + 1) = w_{ij}(t) + \sigma_j(t)(x_i - w_{ij}(t)) \quad (11)$$

The algorithm works as shown in [26], [27] and [28]. However, SOFM algorithms are, firstly, highly dependent on the training data representatives and the initialization of the connection weights. Secondly, they are very computationally expensive since as the dimensions of the data increases, dimension reduction visualization techniques become more important, but unfortunately the time to compute them also increases. For calculating that black and white similarity map, the more neighbors we use to calculate the distance the better similarity map we will get, but the number of distances the algorithm needs to compute increases exponentially.

(2) Fuzzy c-means for image segmentation

The objective of image segmentation is to divide an image into meaningful regions. Errors made at this stage would affect all higher level activities. Therefore, methods that incorporate the uncertainty of object and region definitions and the faithfulness of the features to represent various objects are desirable.

In an ideally segmented image, each region should be homogeneous with respect to some predicate such as gray level or texture, and adjacent regions should have significantly different characteristics or features. More formally, segmentation is the process of partitioning the entire image into $c$ crisp maximally connected regions $\{R_i\}$ such that each $R_i$ is homogeneous with respect to some criteria. In many situations, it is not easy to determine if a pixel should belong to a region or not. This is because the features used to determine homogeneity may not have sharp transitions at region boundaries. To alleviate this situation, we can inset fuzzy set concepts into the segmentation process.

In fuzzy segmentation, each pixel is assigned a membership value in each of the $c$ regions. If the memberships are taken into account while computing properties of regions, we obtain more accurate estimates of region properties. One of the known techniques to obtain such a classification is the FCM algorithm [29, 30]. The FCM algorithm is an unsupervised technique that clusters data by iteratively computing a fuzzy membership function and mean value estimates for each class. The fuzzy membership function, constrained to be between 0 and 1, reflects the degree of similarity between the data value at that location and the prototypical data value, or centroid, of its class. Thus, a high membership value near unity signifies that the data value at that location is close to the centroid of that particular class.

Fuzzy c-means algorithm

The FCM algorithm, also known as Fuzzy ISODATA, is one of the most frequently used methods in pattern recognition.

The FCM algorithm assigns pixels to each category by using fuzzy memberships. Let $X = (x_1, x_2, \ldots, x_N)$ denotes an image with $N$ pixels to be partitioned into $c$ clusters, where $x_i$ represents multispectral (features) data. The algorithm is an iterative optimization that minimizes the cost function defined as follows:

$$J = \sum_{j=1}^{N} \sum_{i=1}^{c} u_{ij}^m \| x_j - v_i \|^2 \quad (12)$$

Where $u_{ij}$ represents the membership of pixel $x_j$ in the $i$th cluster, $v_i$ is the $i$th cluster center, $\| \|$ is a norm metric, and $m$ is a constant. The parameter $m$ controls the fuzziness of the resulting partition, and $m = 2$ is used in this study.

The cost function is minimized when pixels close to the centroid of their clusters are assigned high membership values, and low membership values are assigned to pixels with data far from the centroid. The membership function represents the probability that a pixel belongs to a specific cluster. In the FCM algorithm, the probability is dependent solely on the distance between the pixel and each individual cluster center in the feature domain. The membership functions and cluster centers are updated by the following:

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left( \| x_j - v_k \|^2 \right)^{2/(m-1)}} \quad (13)$$

and

$$v_i = \frac{\sum_{j=1}^{N} u_{ij}^m x_j}{\sum_{j=1}^{N} u_{ij}^m} \quad (14)$$

Starting with an initial guess for each cluster center, the FCM converges to a solution for $v_i$ representing the local minimum or a saddle point of the cost function. Convergence can be detected by comparing the changes in the membership.
function or the cluster center at two successive iteration steps.


Auto adaptive neuro-fuzzy segmentation architecture is presented [31]. The system consists of a multilayer perceptron (MLP)-like network that performs image segmentation by adaptive thresholding of the input image using labels automatically pre-selected by a fuzzy clustering technique. The system's architecture is feedforward, but unlike the conventional MLP the learning is unsupervised. The output status of the network is described as a fuzzy set. Fuzzy entropy is used as a measure of the error of the segmentation system. Given an input image, the system is forced to evolve toward a minimum fuzzy entropy state in order to obtain image segmentation. The system is capable to perform automatic multilevel segmentation of images, based solely on information contained by the image itself. No a priori assumptions whatsoever are made about the image (type, features, contents, stochastic model, etc.). Such a “universal” algorithm is most useful for applications that are supposed to work with different (and possibly initially unknown) types of images.

(4) A Fuzzy Kohonen's Competitive Learning Algorithms for MR Image Segmentation

Kohonen’s self-organizing feature map (SOFM) is a two-layer feedforward competitive learning network, and has been used as a competitive learning clustering algorithm in brain MRI image segmentation. However, most brain MRI images always present overlapping gray-scale intensities for different tissues.

In a Fuzzy Kohonen’s Competitive Learning Algorithms [32], fuzzy methods are integrated with Kohonen’s competitive algorithm to overcome this problem (the name of algorithm F_KCL). The F_KCL algorithm fuses the competitive learning with fuzzy c-means (FCM) cluster characteristic and can improve the segment result effectively.

The comparison between different techniques mentioned above in this paper will doing as shown in figure 4. The MRI image is first segmented using one of the segmentation techniques listed above in this paper. Then the segmented image is separated into three images corresponding to WM, GM, and CSF. Then these images will be compared to the references image using mean squared error to measure the segmentation accuracy.

The MR images used in this paper are obtained from the http://www.bic.mni.mcgill.ca/brainweb web site in Montreal Neurological Institute, McGill University, McConnell Brain Imaging Centre (McBIC) [25]. The database is the result of a research work developed at McBIC and contains quantitative 3D investigation of brain structure and function. The brain phantom and simulated MR images have been made publicly available and can be used to test algorithms such as classification procedures which seek to identify the tissue “type” of each image pixel. The modality, T1-weighted, are downloaded from the website as our experimental data shown in Figure 5. And Figure 6 shows the brain MR image Phantoms. They are considered as the true segmented tissues used in this paper.
and CSF segmentation owes to the Fuzzy Kohonen's Competitive Learning (F-KCL) Algorithms. The segmentation accuracy was measured by using an average overlap metric (AOM) [33], which is quantitative evaluation of performance. Overlap metric is defined for a given voxel class assignment as the sum of the number of voxels that both have the class assignment in each segmentation divided by the sum of voxels where either segmentation has the class assignment. This metric approaches a value of 1.0 for results that are very similar and is near 0.0 when they share no similarly classified voxels.

The AOM measurements for results obtained in different situations are given in Table 4.

### 3. EXPERIMENTAL RESULT

To demonstrate and evaluate the performance of the proposed framework, we mainly applied to simulated MR images. These data were downloaded from brainweb [25]. Experiments have been done under four different conditions that are shown in Figure 11. We first removed the non brain tissue using HWA algorithm, and the IIH correction was used to bring out corrected result. The final result on WM, GM,
Figure 13: The segmented tissues of Image1 using proposed framework.

Figure 14: The segmented tissues of Image2 using proposed framework.

Figure 15: The segmented tissues of Image3 using proposed framework.

Figure 16: The segmented tissues of Image4 using proposed framework.

Table 4: Segmentation results on T1-weighted data under different conditions of noise and IIH

<table>
<thead>
<tr>
<th>Image</th>
<th>Noise</th>
<th>Bias</th>
<th>WM</th>
<th>GM</th>
<th>CSF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image 1</td>
<td>3 %</td>
<td>20 %</td>
<td>0.95</td>
<td>0.88</td>
<td>0.96</td>
</tr>
<tr>
<td>Image 2</td>
<td>5 %</td>
<td>20 %</td>
<td>0.91</td>
<td>0.85</td>
<td>0.94</td>
</tr>
<tr>
<td>Image 3</td>
<td>3 %</td>
<td>40 %</td>
<td>0.93</td>
<td>0.83</td>
<td>0.92</td>
</tr>
<tr>
<td>Image 4</td>
<td>5 %</td>
<td>40 %</td>
<td>0.89</td>
<td>0.82</td>
<td>0.90</td>
</tr>
</tbody>
</table>

According to Zijdenbos’ statement [34] that AOM indicates excellent agreement when it is above 0.7, it can be seen that our system framework is very robust to IIH and noise. Though the accuracy decreased when noise and bias increased, the variance was small and acceptable. Its superiority mainly depended on preprocessing (IIH correction and skull stripping) before segmentation.

4. CONCLUSION

In this paper, a full automatic framework for brain MR image segmentation has been presented. Furthermore, a validation process for MR image segmentation has been demonstrated. It aims to obtain more accurate different tissues with the presence of intensity inhomogeneity (IIH) and noise. The proposed system which firstly receives MRI data, removes non brain tissues using Hybrid Watershed Algorithm (HWA) algorithm, and then correct the intensity inhomogeneity. Then the corrected stripped image is segmented into GM, WM, and CSF using Fuzzy Kohonen's Competitive Learning Algorithms.

Under the quantitative comparison of the performance of four Brain Extraction Algorithm (BEAs) – Brain surface Extractor (BSE), Brain Extraction Tool (BET), Hybrid Watershed Algorithm (HWA) and McStrip - against the "gold standard" of expert manual brain extraction using high-resolution T1-weighted MRI brain volumes, simulation results have shown that HWA algorithm, a hybrid approach incorporating watershed algorithm and deformable model, outperforms BSE, BET, and McStrip, all of which rely on a single algorithmic strategy.

Also under quantitative comparison of the performance of four brain tissue segmentation algorithms – Self organizing Map (SOM), Fuzzy c-means (FCM), Adaptive Neuro-Fuzzy System, and Fuzzy Kohonen's Competitive Learning Algorithms (FKCL)- against the "gold standard". Simulation results have shown that FKCL outperforms other algorithms.

Finally, the proposed system, that firstly receives MRI data, removes non brain tissues using HWA algorithm, then corrects the intensity inhomogeneity. After that, the corrected stripped image is segmented into GM, WM, and CSF using Fuzzy Kohonen's Competitive Learning Algorithms. Tests have been performed and the results have shown that our system framework is very robust to intensity inhomogeneity (IIH) and noise.

References


[33] http://www.cma.mgh.harvard.edu/ibsr/


