Hierarchical Fuzzy Segmentation of Brain MR Images

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ABSTRACT: In brain magnetic resonance (MR) images, image segmentation and 3D visualization are very useful tools for the diagnosis of abnormalities. Segmentation of white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF) is the basic process for 3D visualization of brain MR images. Of the many algorithms, the fuzzy c-means (FCM) technique has been widely used for segmentation of brain MR images. However, the FCM technique does not yield sufficient results under radio frequency (RF) nonuniformity. We propose a hierarchical FCM (HFCM), which provides good segmentation results under RF nonuniformity and does not require any parameter setting. We also generate Talairach templates of the brain that are deformed to 3D brain MR images. Using the deformed templates, only the cerebrum region is extracted from the 3D brain MR images. Then, the proposed HFCM partitions the cerebrum region into WM, GM, and CSF.

I. INTRODUCTION

Various imaging systems provide images including various characteristics of human organs. The magnetic resonance imaging (MRI) system gives valuable information of soft tissues and high-contrast images. In brain magnetic resonance (MR) images, we can diagnose abnormalities through 3D visualizing and quantifying of the interesting part. Object segmentation should be performed for better visualization of 3D objects and, consequently, for more accurate diagnosis.

Many segmentation methods have been introduced (Clark et al., 1995), which can be classified into several categories such as edge detection, thresholding, region growing, template models, random field, and clustering. The edge detection method has limitations when there is noise in the image or when there are complicated textures in the object or background. The threshold method has difficulty in determining the threshold value. The results of the region growing method are dependent upon seed and region of interest that are determined by the operator. The random field method provides good results but usually requires heavy computations. The clustering method produces different results according to the initial centroids and the number of classes.

The fuzzy c-means (FCM) algorithm is a clustering method that has been successfully used for the segmentation of MR images (Yoon et al., 2001). However, the FCM algorithm itself does not solve the problem of the radio frequency (RF) nonuniformity of the MR images, especially when the MR images are obtained in a high magnetic field. Several segmentation methods addressed the RF nonuniformity that resulted in variation of image intensity. The adaptive FCM (AFCM; Pham and Prince, 1999) and the spatial FCM (SFCM; Liew et al., 2000) perform fuzzy segmentation with compensation for RF nonuniformities. The AFCM models RF nonuniformity as a multiplier field, and the SFCM exploits the dissimilarity term, that is, the spatial contextual information of the image. The AFCM requires a manual setting of two parameters \( \lambda_1 \) and \( \lambda_2 \), and the SFCM requires a manual setting of one parameter, \( \sigma \), where the parameter values are defined according to the image characteristics. In addition, the AFCM needs a large computation amount and the SFCM can handle only a small amount of noise and RF nonuniformity.

In general, preprocessing is needed under operator supervision in order to reduce noise and to remove the skull, the eyes, and the cerebellum before segmentation (Yoon et al., 2001; Goebel and Jansma, 2001). As a preprocessing step, Yoon et al. manually draw limit lines around the cerebrum, and Goebel and Jansma distort the image by transformation of the coordinates.

In this article, a preprocessing and segmentation method for brain MR images are proposed. The preprocessing step reduces noise in the MR images and extracts only the cerebrum using Talairach templates. For extraction of the cerebrum, we adaptively match the Talairach templates and the MR images. The proposed hierarchical FCM (HFCM) then classifies the extracted cerebrum into three regions, which are white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF).

In Section II, we introduce the proposed segmentation method. The experimental results using the synthetic image and brain MR...
images are shown in Section III. We conclude the paper in Section IV.

II. THE PROPOSED SEGMENTATION METHOD

The proposed segmentation method is composed of preprocessing and segmentation. An overall block diagram of the proposed method is shown in Figure 1. Details are described in the following subsections.

A. Preprocessing for Noise Reduction and Extraction of Cerebrum.

**Median Filtering.** An image smoothing process is usually applied to make a homogeneous region more homogeneous while keeping the edge and removing the noise. The nonlinear anisotropic diffusion method of Perona and Malik (1990) is widely used for image smoothing. However, the parameters used are dependent on image characteristics, and heavy computation is required due to iteration and many mathematical operations. In this article, therefore, 2D median filtering is used to smooth the brain MR images quickly, which is performed on slice by slice for a 3D image, where the filter size is determined empirically as $3 \times 3$.

**Talairach Transformation.** Human brains are of different sizes, shapes, and positions according to variations in individuals. These individual variations have impeded analysis of brain structures and diagnosis of brain diseases. In 1988, Talairach and Tournoux proposed a proportional grid system to overcome the problem of the individual variations in human brains (Talairach and Tournoux, 1988). They used reference points to set a proportional grid system and to transform a particular brain according to the defined coordinates. They set 27 slices of axial section with an interval of 2–5 mm in the Talairach coordinates. Using the given axial images, we made Talairach templates of the cerebrum and cerebellum in 1-mm intervals.

As Talairach and Tournoux proposed, a brain image is usually transformed into Talairach coordinates based on the midline and eight manually selected points (CA, CP, AP, PP, SP, IP, RP, and LP, as shown in Figure 2). However, transformation of the 3D image into Talairach coordinates can generate interpolation errors. To reduce interpolation error of image in the coordinates transformation, we do not transform the brain image into Talairach coordinates but transform the Talairach templates into the 3D MR image coordinates.

We manually select the locations of 10 points, namely the 8 points mentioned above and the 2 points of ML1 and ML2 (as shown in Figure 2) to define the midline of the coronal section. The hexahedron constructed by AP, PP, SP, IP, RP, and LP is then

Figure 1. Overall block diagram of the proposed segmentation method.

Figure 2. Ten reference points for Talairach coordinates.
divided into 12 hexahedrons using the CA-CP line, the midline, the VCA line, and the VCP line, as shown in Figure 3. The hexahedron is successively divided into 1056 hexahedrons (Talairach and Tour- noux, 1988). Figure 4 shows a sagittal view of the brain where Talairach coordinates have been affine-transformed to the image coordinates. Using the affine-transformed Talairach coordinates, it can be determined whether or not each voxel is included in the right cerebrum template, the left cerebrum templates, or the cerebellum template.

**Template Deformation.** Templates of the cerebrum may not perfectly extract the cerebrum in brain MR images because the shape of an individual brain is slightly different. Therefore, each transformed Talairach template in each slice image is deformed using an active contour (snake) model (Kass et al., 1987). In some slices, the template is composed of more than two regions. These exceptional cases happen in the slices near the top of the brain and in the slices including the cerebellum. In these cases, the initial contours are the deformed templates of the neighbor slices. The initial contour is deformed to the image by minimization of the following energy (Kass et al., 1987):

\[
E = \int_0^1 \left( \alpha |v_s|^2 + \beta |v_{ss}|^2 + E_{ext}(v) \right) ds,
\]

where \(v(s) = (x(s), y(s))\) is the position of the contour and \(v_s(s)\) and \(v_{ss}(s)\) are first and second derivatives of \(v\) with respect to \(s\), respectively. \(\alpha\) and \(\beta\) control the elasticity and rigidity of the contour, respectively, and \(E_{ext}\) is external energy that pulls the contour to the desired position.

For minimization of energy \(E\), Eq. (1) gives the following two independent Euler equations (Kass et al., 1987):

\[
-\alpha x_{ss} + \beta x_{ssss} + \frac{\partial E_{ext}(v)}{\partial x} = 0,
\]

\[
-\alpha y_{ss} + \beta y_{ssss} + \frac{\partial E_{ext}(v)}{\partial y} = 0,
\]

where \(v_s(s) = (x_s(s), y_s(s))\) and \(v_{ss}(s) = (x_{ss}(s), y_{ss}(s))\) are second and fourth derivatives of \(v\) with respect to \(s\), and derivatives of the external energy, \(\frac{\partial E_{ext}(v)}{\partial x}\) and \(\frac{\partial E_{ext}(v)}{\partial y}\), are defined as follows:
Figure 6. Three-dimensional synthetic image.

$$\frac{\partial E_{ext}(v)}{\partial x} = w_{edge} \frac{\partial I(x, y)}{\partial x} - w_{balloonX} \cdot n_x + w_{midline} F_{midline}(x, y) \quad (4)$$

$$\frac{\partial E_{ext}(v)}{\partial y} = w_{edge} \frac{\partial I(x, y)}{\partial y} - w_{balloonY} \cdot n_y + w_{midline} F_{midline}(x, y) \quad (5)$$

In Eqs. (4) and (5), $I(x, y)$ is the image value at $(x, y)$ and $w_{edge}$ is weighting parameter to control the external force.

As an external force in this article, an image gradient from the Sobel operator (Jain, 1989) is used. However, additional forces are needed to extract only the cerebrum. Because the initial contour of the template sometimes exists between the GM and the CSF or between the skin and the background, the snake algorithm cannot lead to an appropriate result. Therefore, the initial contour is shrunk with a given ratio $R_{sh}$, and the pressure force like balloon (Cohen, 1991) is applied to the shrunk contour. The shrunk contour is expanded in the direction of its normal vectors, and the expansion stops at the local maximum of the image gradient. At the axial slices that include the corpus callosum, the right and left cerebrum templates can be deformed over the other part of the cerebrum because the left and right cerebrums are connected by the corpus callosum. To prevent the over-deformation, we define a midline force that prevents the contour from expanding over the midline. Derivatives of the external energy of Eqs. (4) and (5) are modified in this article as follows:

$$\frac{\partial E_{ext}(v)}{\partial x} = w_{edge} \frac{\partial I(x, y)}{\partial x} - w_{balloonX} \cdot n_x + w_{midline} F_{midline}(x, y) \quad (6)$$

$$\frac{\partial E_{ext}(v)}{\partial y} = w_{edge} \frac{\partial I(x, y)}{\partial y} - w_{balloonY} \cdot n_y + w_{midline} F_{midline}(x, y) \quad (7)$$

where $w_{balloonX}$, $w_{balloonY}$, and $w_{midline}$ are weighting parameters to control the external force, $n_x$ and $n_y$ are the $x$ component and $y$ component of the unit normal vector of the contour at $(x, y)$, respectively, and $F_{midline}$ is the midline force, which is defined as follows:

$$F_{midline}(x, y) = \begin{cases} 
-1.0, & (x, y) \text{ is on midline of the left cerebrum template.} \\
1.0, & (x, y) \text{ is on midline of the right cerebrum template.} \\
0.0, & \text{otherwise.}
\end{cases} \quad (8)$$

It is necessary to set parameters such as $\alpha$, $\beta$, $w_{edge}$, $w_{balloonX}$, $w_{balloonY}$, $w_{midline}$, $R_{sh}$, the number of contour points $p$, and the number of iterations. In the experiments, $\alpha$ is 0.1, $\beta$ is 0.0, $w_{midline}$ is 1.0, $p$ is a quarter of the number of the initial contour pixels, and the number of iterations is 50. For images with a single-region template, $w_{edge}$ is 3.0, $w_{balloonX}$ is 0.2, $w_{balloonY}$ is 0.2, and $R_{sh}$ is 0.8. In images with a multiple-region template, the deformed template of the upper and lower slice is used as the initial contour. Thus, different parameters are applied to the images with multiple-region template as $w_{edge}$ is 2.0, $w_{balloonX}$ is 0.1, $w_{balloonY}$ is 0.2, and $R_{sh}$ is 0.95.

B. The Proposed Hierarchical Fuzzy C-means Method.

The FCM classifies every image pixel into $C$ subgroups, where the image pixels inside a subgroup show a certain degree of closeness or similarity (Gath and Geva, 1989). However, there are a couple of observations to note (Tolias and Panas, 1998). First, the centroid values are constant for the entire data set, so that the FCM cannot adapt to a nonstationary image such as a high field MR image with RF nonuniformity. Second, the FCM does not provide good segmentation if the regions to be segmented have a large dynamic range of intensities.

The proposed HFCM processes the FCM in a small volume that is hierarchically divided from the original 3D data set and calculates the degrees of membership for each volume. In a small volume, the volume can be approximated as stationary even if the overall image is not stationary.

In our application, there are three subgroups, namely WM, GM, and CSF. The overall segmentation procedure, which is shown in Figure 1, is described as follows:

![Image of segmentation results](image-url)

Figure 7. Two selected slices of the synthetic image (top) and their segmented results (middle and bottom) from FCM and HFCM (left: $z = 37$, right: $z = 199$).
Figure 8. The misclassification ratio of FCM and HFCM in the synthetic image.

Figure 9. Four selected slices of a 3D brain MR image and the cerebrum templates: (a) selected brain MR images, (b) corresponding templates of cerebrum before deformation, and (c) templates of cerebrum after deformation.

Figure 10. The deformed templates before and after removal of the cerebellum: (a) cerebrum templates before deformation, (b) cerebrum templates after deformation, (c) cerebellum template before deformation, (d) cerebellum template after deformation, and (e) cerebrum templates after removing cerebellum template.
and their distorted images of data 2 and data 3.

Figure 11. Two selected slices of the homogeneous image (data 1) and their distorted images of data 2 and data 3.

1. Calculate the mean (mean) and standard deviation (std) of the original 3D data to define the initial centroids of the HFCM. In a $T_1$-weighted brain MR image, the intensity of WM is higher than those of GM and CSF, and the intensity of GM is higher than that of CSF. Thus, we define the initial centroid of WM, $\beta_1 = \text{mean + std}$; that of GM, $\beta_2 = \text{mean}$; and that of CSF, $\beta_3 = \text{mean - std}$. The initial degrees of membership are all zero.

The hierarchical level $r$ is initially set as one. At the first level, the volume ($V$) is the overall 3D data set.

2. Execute the FCM for each volume at hierarchical level $r$. The membership values are computed as follows:

$$ u_{ij}^r = \frac{1}{\sum_{k=1}^{3} \frac{1}{d^2(X_i, \beta_k)}} \quad \text{for } i, j = 1, 2, 3, (9) $$

where $u_{ij}^r$ is degrees of membership of the $j$th voxel in the $i$th subgroup at the $r$th hierarchical level, $X_i$ is intensity of the $j$th voxel, $\beta$ is the centroid of the $i$th subgroup, and $d(X_i, \beta_j)$ is intensity difference between $X_i$ and $\beta_j$. New centroids are then computed from the computed membership values as follows:

$$ \beta_i = \frac{\sum_{j=1}^{Np} (u_{ij}^r)^2 X_j}{\sum_{j=1}^{Np} (u_{ij}^r)^2}. \quad (10) $$

3. Divide each volume at level $r$ into eight smaller volumes, as shown in Figure 5. If the size of the divided volume $V$ becomes smaller than $8 \times 8 \times 8$, stop the iteration and go to step 4. Otherwise, increase the hierarchical level, $r \leftarrow r + 1$, and go to step 2.

4. As the hierarchical level increases, the volumes become smaller and the number of voxels in a volume is not enough for reliable estimation of degrees of membership and centroids. Therefore, the membership values from every level are averaged with different weights according to the level and are normalized as follows:

$$ u_i = \frac{\sum_{k=1}^{3} \frac{1}{k} u_{ij}^k}{\sum_{k=1}^{3} \sum_{j=1}^{Np} \frac{1}{k} u_{ij}^k}. \quad (12) $$

5. Perform hard segmentation using the normalized membership values, i.e., assign every voxel to the cluster that corresponds to the maximum degrees of membership, so that each voxel is classified into one of WM, GM, and CSF.

### III. EXPERIMENTAL RESULTS

The proposed segmentation method was implemented using a 2 GHz Pentium IV with 512 MB memory and Visual C++. First of all, the HFCM was applied to the synthetic image, which is similar to the one used in Pham and Prince (1999). The synthetic image is the 3D checkerboard as shown in Figure 6 with sinusoidal intensity variation, and the matrix size is $256 \times 256 \times 256$. The “C” program for making the synthetic image is given as follows:

```c
int \phi; // the phase (40 in this experiment)
int Np; // the length corresponding [0–2\pi] of cosine function (180 in this experiment)
int x, y, z; // the coordinates
BYTE value; // synthetic image value
for (z = 0; z < 256; z++){
    for (y = 0; y < 256; y++){
        for (x = 0; x < 256; x++){
            if (((x/100) + (y/100) + (z/100))%2 == 0)
                value = I_H;
            else
                value = I_L;
            value += (BYTE)(amp*cos(2\pi(x - \phi/Np)))*cos(2\pi(y - \phi/Np))cos(2\pi(z - \phi/Np));
        }
    }
}
```

As mentioned in Tolias and Panas (1998), the FCM converges to adequate centroids if all three clusters are in the volume. Otherwise, the distances between the two different clusters may be 0, and the degrees of membership have infinite solutions. Therefore, we need to confirm validity of the membership as follows:

$$ u_{ij}^r = \begin{cases} u_{ij}^r, & \text{if } \beta_1 > \beta_2 > \beta_3 \\ 0, & \text{otherwise} \end{cases} \quad (11) $$
The synthetic image has two subgroups with high intensity \( I_H \) in white and low intensity \( I_L \) in black as shown in Figure 6. The amplitude of sinusoidal intensity variation is \( amp \), then \( I_H \) is \( (255 - amp) \) and \( I_L \) is \( (amp) \). The maximum intensity of the low intensity subgroup is \( (2 \times \text{amp}) \) and the minimum intensity of the high-intensity subgroup is \( [255 - (2 \times \text{amp})] \), thus the maximum intensity of the low-intensity subgroup can be higher than the minimum intensity of the high-intensity subgroup at a high variation of \( \frac{\text{amp}}{\text{H11022}} \leq 66 \). Figure 7 shows the two selected slices, where \( z \) is 37 in the left panel and \( z \) is 199 in the right panel, at \( \text{amp} = 75 \), and their segmented results of high-intensity class from FCM and HFCM. The segmented results from FCM shows some misclassification, whereas the HFCM shows good segmentation results. The ratios of misclassification from FCM and HFCM are shown in Figure 8 with respect to \( \text{amp} \), where the misclassified ratio denotes the ratio between the number of misclassified voxels and the total number of voxels.

Next experiments were performed with the brain MR images, which were obtained by using a 3D magnetization prepared rapid acquisition gradient echo (MP-RAGE) technique to enhance the contrast between WM and GM, and to reduce the scan time. Data 1 was the sample data of the BrainVoyager software (Goebel and Jansma, 2001) from a Siemens 1.5 Tesla MRI system. For data 1, TR was 9.7 ms, TE was 4.0 ms, and the matrix size was \( 256 \times 256 \times 256 \). Four slices of data 1 are selectively shown in Figure 9(a). After 10 reference points are set, the transformed Talairach templates are shown in the white region as shown in Figure 9(b). Figure 9(c) shows the deformed cerebrum templates. In the fourth row image of Figure 9(c), the template contains the cerebellum because the boundary between the cerebellum and the cerebrum is ambiguous. This makes it necessary to deform the cerebrum template and remove the cerebellum region from the cerebrum templates, as shown in Figure 10.

As used in AFCM (Pham and Prince, 1999), the original image is distorted by adding the artificial multiplier field as follows:

\[
m_i(x, y, z) = A(ax + 1)^2,
\]

where \( (x, y, z) \) is the 3D coordinate of the images when \( (0, 0, 0) \) is the center of the image, and \( a \) and \( A \) are the distortion parameters to control the smoothness and magnitude of distortion, respectively. Data 2 and data 3 are the images distorted from data 1 in only anterior-posterior direction and diagonal direction, respectively. Figure 11 shows the two selected slices of data 1, data 2, and data 3, where the distortion parameters for data 2 and data 3 are given as \( A = 20 \) and \( a = (1/128) \). The FCM and the
proposed HFCM are applied to the original and the distorted images using deformed templates of the original images. The segmented WM from FCM and HFCM are shown in Figure 12. For data 2 and data 3, HFCM does not segment the WM well because of the high distortion; however, HFCM segments even small branches of WM that FCM does not.

When $a$ is defined by a function of $b$ as $\frac{1}{(128/H_1)^b}$, $b$ varies from 1 to 10, and $A$ varies from 10 to 40, the misclassification ratios of segmented WM from FCM and HFCM are shown in Figure 13. In the analysis of the brain MR images, the reference subgroups are the classified results of data 1. Thus, the misclassification ratio is defined as the ratio between the number of misclassified WM voxels of data 2 and the total number of WM voxels classified from data 1.

The left and right columns of Figure 14 show the selected two slices from three brain MR images of data 1, data 4, and data 5, respectively. Data 4 and data 5 were obtained from our 3-Tesla MRI system at the KAIST fMRI center, Korea. For data 4 and data 5, TR was 10 ms, TE was 4.0 ms, and the matrix size was $256 \times 256 \times 128$. In data 4 and data 5, there is some RF nonuniformity in the head boundary. First of all, preprocessing is performed on each image. Table I shows the computation time for the Talairach transformation and template deformation. The seg-

Table I. Computation time for Talairach transformation and template deformation.

<table>
<thead>
<tr>
<th></th>
<th>Data 1</th>
<th>Data 4</th>
<th>Data 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Talairach transformation</td>
<td>6.33 s</td>
<td>6.37 s</td>
<td>5.01 s</td>
</tr>
<tr>
<td>Template deformation</td>
<td>20.18 s</td>
<td>21.57 s</td>
<td>14.85 s</td>
</tr>
</tbody>
</table>

Figure 13. Misclassification ratios of FCM and HFCM in the brain MR of data 2 when (a) $A = 10$, (b) $A = 20$, (c) $A = 30$, and (d) $A = 40$.

Figure 14. Two selected slices (left and right columns) of data 1, data 4, and data 5.
Figure 15. Segmentation results from the HFCM: (a) data 1, (b) data 4, and (c) data 5.
mentation results from the HFCM are shown in Figure 15 where input images are shown in Figure 14. The segmented WM from the FCM, the SFCM, the AFCM, and the proposed HFCM, which are applied to the same pre-processed images, are shown in Figure 16. In the SFCM, $\sigma$ of $\lambda$ was 20. In the AFCM, $\lambda_1$ and $\lambda_2$ affected the segmented results and the computation amount. They should be set in the AFCM to iterate less than 50 times (Pham and Prince, 1999). However, it is difficult to find appropriate values. $\lambda_1$ and $\lambda_2$ are 1900 and 2400 in data 1, 1000 and 1500 in data 4, and 130 and 1000 in data 5. With those parameters, the iteration number is 35 in data 1, 141 in data 4, and 180 in data 5. The segmentation results of data 1 are almost the same for all methods, because data 1 do not have RF nonuniformity. However, the segmentation results of data 4 and data 5 are different for each segmentation method. The FCM, SFCM, and AFCM cannot segment the WM region well near the head boundary because of the RF nonuniformity. Table II shows the iteration number per volume and the computation time of the various segmentation methods for data 1. The iteration number and the computation time of the FCM and SFCM are very small; however, they could not solve the RF nonuniformity problem.

IV. CONCLUSION

The proposed HFCM improves the segmentation performance of the FCM in nonstationary images. The HFCM is executed without user intervention, and it does not require any parameter setting. The HFCM segments WM, GM, and CSF well, even though images are distorted by RF nonuniformity. In addition, semi-automatic preprocessing is used in which the user needs to set just 10 reference points on 3D MR images to draw the Talairach coordinates. This manual setting of the 10 reference points can be performed automatically by further research. Although some parameters are needed for template deformation, they are not so sensitive to image intensity variations. The deformed templates enable the segmented regions to include only the cerebrum area.

Figure 16. Segmented WM from the FCM, the SFCM, the AFCM, and the HFCM: (a) data 1, (b) data 4, and (c) data 5.
Table II. Iteration number per volume and computation time of FCM, SFCM, AFCM, and the proposed HFCM.

<table>
<thead>
<tr>
<th>Method</th>
<th>Iteration Number</th>
<th>Computation Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCM</td>
<td>5</td>
<td>1.38</td>
</tr>
<tr>
<td>SFCM</td>
<td>5</td>
<td>6.25</td>
</tr>
<tr>
<td>AFCM</td>
<td>35</td>
<td>62.61</td>
</tr>
<tr>
<td>HFCM</td>
<td>1.03/volume</td>
<td>11.72</td>
</tr>
</tbody>
</table>

REFERENCES


