Automated separation of gray and white matter in brain MRIs by fastened segments of geodesic contours

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Abstract: Gray matter (GM) and white matter (WM) are adjacent tissues in the brain separated by an interface. Extraction of this boundary is very important for quantitative analysis and monitoring of atrophy. A perfect capture for this purpose is a missing vital item for which research continues. In order to get close to such precision, two novel systems are presented for segmentation of cortical GM and WM in brain MRIs. The system imitates human perceptual sensitiveness to contrast, which is the basic principle of edge detection algorithms, and completes its shortcoming feature of segmentation. As well as being completely automatic, the system is also unsupervised. The correct GM-WM boundary rate gets close to 77% and the segmentation accuracy is over 95%, which are promising results. In comparison tests with SPM, the proposed technique showed 6% higher accuracy with both noisy and normal data and better recovery of small cavities in sulci, being confirmed by experts’ drawings.

Key words: Atrophy, geodesic contours, MRI, gray matter, segmentation

1. Introduction

Two main tissues in the brain are gray matter (GM) and white matter (WM). Accurate and quantitative information about them is important for the diagnosis of particular diseases such as Alzheimer disease, multiple sclerosis, and ischemic infarcts that cause atrophy as normal aging does. Cerebral atrophy is a volume loss in varying amounts in these main tissues and must be measured.

A generally observed situation in visits to clinics is that overly busy radiologists have no time for manually tracking the GM-WM interfaces, which would be the most reliable measure of tissue features. Inter-user and intra-user variations in boundary extraction also exist, which destroy reproducibility. Thus, automated segmentation is put forward as a solution of computer-aided diagnosis. Reliability concerns then come up at the exact separation of gray and white matter [1].

Many techniques are put forward for accurate segmentation. When automaticity is introduced as a feature, machine learning algorithms such as support vector machines [2], geodesic contours [3,4], neural networks [5,6], and many others exist in the literature. These studies led to software packages like SPM [7], ITK [8], and FSL [9]. Many of these algorithms are listed [10] and compared according to their accuracies and speeds [11].

There is not a perfect capture of tissues automatically because of inhomogeneities and other noises in images. While measuring atrophy in sulcal/gyral regions, the performances of the above algorithms get even worse. For instance, Kochunov et al. [12] measured atrophy in 14 cortical sulcal regions by applying existing

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segmentation techniques for recovering from inhomogeneity and admitted that automatic segmentation accuracy was unavoidably on the order of 77%.

When modalities are concerned, the algorithms mostly use T1 images [4,11], which are anatomically easier to segment than T2 images. Their weakness is that they are mostly based on intensity inhomogeneities and partial volume (PV) effects, which need a separate recovery. Many papers were put forward for just treating inhomogeneities [13,14].

When atrophy is the subject of investigation, the exact capture of borders at sulcal and gyral cavities have very high importance. In order to notice the propagation of atrophy in a certain sulcus or gyri, error margins have to be much lower than the atrophic progress. The better the precision for detection of borders is and the less the error is, the earlier and the more accurate the atrophy detection will be. A full automatic separation of GM-WM tissues in single modality with high precision for the whole brain volume is still absent and a vital work, especially for quantitative atrophy [1,12].

Multimodality (T1, T2, and PD MRI) will probably help for better segmentation. However, no patient will stand just for it for a long time, which is an impractical solution. On the other hand, an expert’s eyes are capable of diagnosing in a single modality as in this study, where GM-WM is captured from both T1 and T2 weighted data.

In this paper, we identify the GM-WM interface in both T1 and T2 weighted MR images nearly as precisely as a radiologist. This is done by utilizing geodesic passive contours (GPCs) with two novel algorithms first presented at a conference [15]. The sensitiveness of human eyes to the edges is imitated and a seamless border is extracted without getting confused with the regional variation of the intensity. It is well known that a human observer is capable of tracking even a weak edge by looking at the relative contrast around it and similar patterns to the tracking process that is going on. That property has been brought into machine vision by usage of the geodesics because this attitude is inherently present in the cooperation of the adjacent geodesics.

Geodesics have such behavior since they possess basic atlas features of the real GM-WM boundary. Circularity, being a long closed contour, and forming a railway pattern with adjacent geodesics are the features that make geodesics valuable for cortical tissue segmentation because the GM-WM boundary exactly possesses these three properties. These geodesics are not active or evolving as mentioned in two recent two studies [15,16].

Edge detection algorithms are also sensitive to the edges and find them well. Nevertheless, being based on the gradient as a local feature, no global or spatial information like atlas information or the sought pattern is used. That can be seen in the region encircled with an ellipse in Figure 1, where a strong edge in the GM-WM border tends to extend and merge with another edge segment in the WM-CSF border. Two borders are then mixed and confusing. Moreover, disconnected edge segments exist because of weak contrast in the rectangular region. However, geodesics do good segmentation in both cases, trace the true boundary, and produce closed curves.

That is why edge detection can only be a preprocessing of segmentation and FSGPC algorithms can combine the perceptual edge sensitiveness of humans with segmentation.

2. Method
2.1. Automated separation of gray and white matter on brain MRIs by FSGPC
Choosing the beneficial segments of geodesics is the main goal that the following algorithms try to achieve. First, equally separated geodesics with different lengths as in Figure 2a are drawn with a step size determined as in Figure 2b beginning from the WM (thought of as sea level) up to CSF (peak) in T2w as in Figure 2c. The FSGPC algorithms are then applied.
Figure 1. (a) GM-WM boundary, observed in normal T2 MRI as a coastal band. (b) Edge detection algorithms and their resulting blue discontinuous edges. Good tissue segmentation by FSGPC with closed geodesics at correct tissue borders.

Figure 2. (a) Lengths of 15 geodesics inside BSC with numbers of points they have at vertical axis. Peak at 4th geodesic contour shows the existence of the GM-WM border. (b) Longest geodesic and its 4 pixel (red line) neighborhood. (c) Monotone increasing nature of geodesics from WM to CSF.

The intensity of a particular tissue is not homogeneous and it shows small fluctuations. There are two main reasons for that. First, the intensity gradually increases from the WM to the CSF at the border zone. This gradient is normal for the GM-WM interface and apparent when geodesics are drawn, as in Figure 2c. Second, by moving along the GM-WM border, the intensity may also change because of inhomogeneity and PV effects. Thus, a single geodesic is inadequate for segmentation. One geodesic contour that captures the border very well at one sulcus can badly trace the border at a nearby sulcus. That gradual increase of intensity in the normal direction encourages the usage of geodesics and sets off this research.

2.2. Underlying algorithms

All the segmented tissues are at the inner side of the brain surface contour (BSC). Thus, nonbrain tissues must be removed by a skull-stripping algorithm [15]. Comparison of the brain extraction algorithms can be found in
After the brain is well extracted, the length of the BSC is taken as a criterion for removing overly small contours inside it. The BSC is thickened so that none of the geodesics can escape through it and geodesics are surely inside.

2.3. Determination of step size

Identification of the step size is done automatically. This is shown in the following algorithm. A distance of one pixel is taken in the normal direction to mother points on the geodesic curve. These new child points possibly have new intensities. These child points are subtracted from mothers and the mean (red line in Figure 2b) of these intensity differences will be the threshold for the step size not covering most of the children. Thus, a larger step size covering statistically 95% of child points will be adequate and adjusted automatically for all other brain MRI data with probably different tissue intensities.

Step size identification [15]:

1. Find longest geodesic contour in BSC; store its points
   \[ C = \{(x,y) : I(x,y) = \text{intensity of that geodesic}\} \]
   \[ C = \{P_{i1}, P_{i2}, P_{i3}, \ldots \} \]

2. Calculate normals on each contour \( C_i \) point
   \[ N_{ij} = (-1) \times (P_{ij-1} - P_{ij+1}) \]

3. Go in normal (towards CSF tissue) direction to each contour point on \( C_i \)
   i. \( k = 1 \) (\( k \) pixels perpendicular to \( C_i \))
   ii. \( \Delta_{normal} = N_{ij} \times k \)
   iii. \( P_{new} = P_{ij} + \Delta_{normal} \)
   iv. \( S_i = \{S_i + P_{new} \} \)

4. Step size > mean of intensities of points in set \( \{S\} \)

2.4. Extraction of GM-WM boundary with FSGPC-I

One geodesic may produce many separate level sets at that fixed intensity, as in Figure 2c. The FSGPC progresses pointwise. It must be sure that contour points of those closed loops are really edge points on the GM-WM interface. Thus, the FSGPC eliminates false positive edges by the criteria that their normals do not point out a higher geodesic in the vicinity of \( W_{GM} \) (width of gray matter, 2 to 4 mm thick).

On the other hand, an upper geodesic in the vicinity of \( W_{GM} \) will persuade the algorithm that the point is on the GM-WM border. For that purpose, pointwise normals to the current geodesic are obtained. For each point in the current geodesic, a close point from an upper geodesic inside \( W_{GM} \) is tried to be found in the normal direction. Similar points that maintain the criteria are added together to form segments. Missing points are completed from the same contour to constitute a continuous and smooth curve. After finishing that new segment, upper parallel segments in the hinterland of this new one are deleted. The hinterland concept
is important and can be better understood from Figure 3, where blue segments constitute hinterland segments from hinterland geodesics and are of no further use and should be deleted. Hinterland geodesics are not totally deleted, on the other hand. Missing segments of the tissue interface will be supplied by using the same procedure for these undeleted upper geodesics. Figure 3 is elaborative and illustrates that procedure.

**Figure 3.** (a) First geodesic, its red-colored part, chosen for GM-WM boundary. Discarded yellow parts lacking ridged background. Deleted blue segments of higher geodesics at hinterland of red segment. (b) Missing segment of GM-WM being completed by yellow segment from upper geodesic. (c) The junctions encircled with green circles providing continuity. (d) Resulting patchy boundary.

At step 7, \( C_i \) is shortened very much because of deleting the segments, which are impossible to contribute to the boundary. They are useless since a parallel segment of a lower geodesic has already been marked as segment of the GM-WM boundary. The algorithm works fast, because after the first contributions to boundary, most parts of the remaining upper geodesic contours are deleted. This deletion goes on at every loop between steps 3 and 7.
Algorithm FSGPC-I:

1. Define geodesic contour gray values
   \[ G_i = i, \text{ where } i \in S, S = (1, 2, \ldots, 256/\text{Stepsize}) \]

2. Find geodesic contours
   \[ C_i = \{ (x, y) : I(x, y) = G_i \} \]
   \[ C_i = \{ P_{i1}, P_{i2}, P_{i3}, \ldots \} \] contour points

3. ∀ contour point on \( C_i \), calculate normals
   \[ N_{ij} = (-1) \times (P_{ij} - P_{ij+1}) \]

4. Go in the normal direction to point on \( C_i \), look for a higher geodesic in \( W_{GM} \).
   While \( \Delta_{normal} < W_{GM} \) (width of gray matter)
   i. \( k = k + 1 \) (k grid units perpendicular to \( C_i \))
   ii. \( \Delta_{normal} = N_{ij} \times k \)
   iii. \( P_{new} = P_{ij} + \Delta_{normal} \)
   iv. If \( I(P_{new}) > \text{Stepsize} \) (check if there is a geodesic in \( W_{GM} \))
       \( B_i = \{ B_i + P_{new} \epsilon B_i \} \), note \( B_i \) as the GM-WM boundary
       Break;

5. Fill the small gaps of \( B_i \) with points of \( C_i \)

6. Delete the higher geodesics’ segments at hinterland of \( B_i \)
   a. \( s_{ij} \) = set of connected points on \( B_i \) in one segment
   b. Label the first and ending points of each group defining a segment
   c. ∀ \( s_{ij} \) on \( B_i \)
      Clear the segments of upper geodesics
      i. ∀ geodesic after \( C_k \), \( k = i, i+1, \ldots \)
      ii. Find closest points on \( C_k \) to \( s_{ij} \) to form \( s_{kj} \)
      iii. Delete the segment \( s_{kj} \) between these two points
      iv. \( C_k = C_k - s_{kj} \)
      v. \( k = k + 1 \) (update to get to index of upper geodesic)
     vi. Go to step 6.c.i to clear segments \( s_{kj} \) at upper geodesics
   d. Go to 6.c to get the next segment and delete the hinterland segment

7. Go to Step 3, increment \( i \), and get next \( C_i \)

8. Making junctions (connect all collected segments from different geodesic contours)

For finer tuning, the above algorithm can be called again by halving the step size. There will be little movement on the boundary. The actual GM is the region covering the area between the outer white BSC and the patchy continuous contour. Thus, irrelevant inner extensions of segments or some few folded parts will not disturb the cortical GM-WM separation.
2.5. Extraction of GM-WM boundary with FSGPC-II

Although the above algorithm works fairly well, certain constraints like $\Delta_{\text{normal}} < W_{GM}$ require a priori knowledge about the width of the GM, which is a known quantity and has a value approximately between 2 mm and 4 mm. However, atrophy may also take place in the GM, as mentioned in [18]. Thus, an alternative full automatic algorithm, FSGPC-II, is developed for capturing the same border and segments of two tissues. The railway pattern of inner and outer borders of the GM is the key issue in this method. Geodesics inside the BSC are never deleted as far as they have an adjacent parallel geodesic (conjugate geodesic). Thus, the FSGPC-II does not work pointwise except at cavities and normals to points are not calculated. Thus, it is a simpler and faster algorithm, skipping steps 3–5, and the pseudocode is given in the following algorithm. Parallelism between close geodesics is utilized in the FSGPC-II instead of looking for a conjugate geodesic in the proximity of $W_{GM}$ in FSGPC-I.

![Figure 4](image)

Figure 4. First row: addition of geodesics right to left. Red geodesic is not looped since its segment at the hinterland of the green lower geodesic is deleted, so as the yellow one. Second row: addition of cavities of each geodesic. Last row: cavities and geodesics, all added. Final GM-MW tissue separation in (h) and (i) [15].
Algorithm FSGPC-II [15]:

1. \( B_i = C_i (\forall \text{geodesic adds up to construct GM-WM boundary}) \)

2. Delete the upper geodesics' segments at hinterland of \( B_i \)
   a. \( s_{ij} = \text{connected points on } B_i \)
   b. \( \forall S_{ij} \) on \( B_i \), delete the hinterland segments
      i. \( \forall \text{geodesic after } C_k, k = i, i+1, \ldots \)
      ii. Find closest points on \( C_k \) to \( s_{ij} \) and call it \( s_{kj} \)
      iii. \( C_k = C_k - s_{kj} \) (\( s_{kj} \) is deleted)
      iv. \( k = k + 1 \)
   c. Go to 2.b: get the next segment and delete the hinterland of it

3. \( \forall \text{Cavity on } B_i = C_i \)
   a. \( \mathcal{L}(C_i, C_{i+1}) = \text{Nonparallel points} \)
   b. \( W_m = \forall \text{connected points on } \mathcal{L}(C_i, C_{i+1}) \)
   c. \( \forall W_m \)
   d. If \( W_m \epsilon C_{i+1} \)

Delete \( W_m \)
Else
   i. \( k = i + 2 \) (get upper geodesic of \( W_m \))
   ii. Cavity edges = \( W_m \) (initialization)
   iii. Find \( H_k \), hinterland on \( C_k \) to \( W_m \)
   iv. Cavity edges = cavity edges + // points from \( \mathcal{L}(H_k, W_m) \)
   v. \( W_m = W_m + NP \) points from function \( \mathcal{L}(H_k, W_m) \)
   vi. \( k = k + 1 \)
   vii. Go to 3.e.iii

4. Go to Step 1: increment \( i \) & get next \( C_i = B_i \)

Figure 4 is elucidative for better understanding the above algorithm. After beginning with the shortest and innermost geodesic in Figure 4a, higher intensity geodesics are articulated to it as in Figures 4b and 4c. Cavity recovery is shown in the second row for each of the three geodesics in the same column. Finally, the resulting GM-WM borders are given accordingly in purple at the corresponding columns and cortical tissue segmentation is highlighted in the last row.

The underlying geometric model for detecting parallelism is shown in Figure 5a by which cavities are fine-tuned. Assume that \( C_i \) and \( C_{i+1} \) are two adjacent geodesics and assign \( B_i = C_i \), since \( C_i \) is certainly a segment of GM-WM. The \( \mathcal{L}(C_i, C_{i+1}) \) function then categorizes the points on \( C_{i+1} \) as being parallel (P) or
nonparallel (NP). For each contour point on \( C_{i+1} \), like \( F \) in Figure 5a, \( E \) and \( D \) as in Eq. (1) and Eq. (2) are determined as points on \( C_i \) with minimum distance to \( F \) on \( C_{i+1} \). In the expression \((x: y, i)\), \( x-y \) denotes the spatial coordinates of that contour point in the image and \( i \) denotes the ordering of that point among other contour points. \( g.c \) is the abbreviation of geodesic.

\[
Es.t|FE| = \min_{i=1,2,...,\text{end}} \left( \sqrt{(g.c60(x : y, i)^2 - F(x : y)^2)} \right)
\]

\[
Ds.t|ED| = \min_{i=1,2,...,\text{end}} \left( \sqrt{(g.c68(x : y, i)^2 - E(x : y)^2)} \right)
\]

\[
\text{If } |FE| \geq |ED| + 1 \quad F \text{ is parallel}
\]

\[
\text{else} \quad F \text{ is NP}
\]

If \( F \) is found to be nonparallel in Eq. (3), it is added to the NP set. NP set \( C_{i+1} \) is then obviously a cavity and needs a separate recovery. That cavity may have nontouching edge segments called \( W_m \) where each segment is formed of points in connection. In Figure 5a, \( W_m \) is colored blue. Higher intensity g.c. 76 in green is determined at the hinterland of \( W_m \). Recursively these blue and green segments are investigated to see whether these lines are parallel. If not, that is another cavity to be treated. The algorithm deepens until blue segments are backed with parallel green lines or there are no more higher geodesics. Red dashed lines will be added to the GM-WM border and increase the precision there as shown in Figure 5b.

3. Materials and database

In the hospitals from which the data were obtained, 1.5 T MR is used. Slices generally have 5 mm width and dependent amounts of interslice gaps. There exist over 100 different patients in the database. T1 and T2 MRI volumes in DICOM format are present in these data. Images are automatically processed by the algorithm slice by slice. Seven slices of 20 MRI volumes of the patients are utilized. Echo time, \( TE = 4.44 \text{ ms} \), \( TR = 1160 \text{ ms} \), and flip angle (FA) \( = 15^\circ \) are chosen as a standard sequence of T1 weighted imaging.
FOV may differ from one patient to another but usually varies between 212 mm × 176 mm and 238 mm × 198 mm. When this slice is figured by MATLAB, the frame size turns to 670 × 564 grid units. For fast processing, that frame is resized in 448 × 376 grid units, thus lowering its size by a factor of 3/2. Thus, working resolution is \( \frac{212}{448} = \frac{176}{376} = 0.47 \) mm or \( 0.47 \times 0.47 = 0.22 \text{ mm}^2 \).

4. Validation

Most papers utilize public test databases like the Internet Brain Segmentation Repository as a common base to compare their algorithms. However, the real data there involve only T1 images and not T2 since T2 is rarely used in segmentation. This also shows the difficulty in T2 weighted images. First, real data in this research are used and a comparison is made according to resulting accuracy scores in the literature. Visual inspection by experts is applied as a second validation method based on comparing their manual drawings with the produced results. Moreover, BrainWeb [19,20] synthetic data serve as common data to compare the FSGPC with SPM on the ground-truth given by BrainWeb.

4.1. Validation by visualization

Two experts with whom we work evaluated the segmentation results and agreed on the high precision of the algorithms. Randomly chosen segmented images are displayed to get an opinion about the efficiency of the system. The extracted interfaces, GM-WM and CSF-GM boundaries, are mounted on those images.

4.2. Validation by overlap metrics

A cross-correlation matrix is filled by comparing the FSGPC-II algorithm with Expert 1 and Expert 2. The entities of the matrix are filled by values obtained in the steps as visualized in Figure 6. The segmented area of WM by FSGPC is prepared as in Figures 6a and 6b. In Figure 6c the WM is obvious and the area between the BSC and WM is constituted by the CSF and GM combination in unique color. Experts’ drawings are prepared in the second row of Figures 6d and 6e and are overlapped in Figure 6f. The last row displays the overlapping of experts and FSGPC according to both boundary and area. In Figure 6f all three outputs are in different colors, orange, green, and brown, on a blue BSA. Knowing the values at each step, Table 1 is easily constructed for each slice.

<table>
<thead>
<tr>
<th></th>
<th>WM Exp 1</th>
<th>GM&amp;CSF Exp 1</th>
<th>WM Exp 2</th>
<th>GM&amp;CSF Exp 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>WM FSGPC-II</td>
<td>TP</td>
<td>FP</td>
<td>TP</td>
<td>FP</td>
</tr>
<tr>
<td>GM&amp;CSF FSGPC-II</td>
<td>FN</td>
<td>TN</td>
<td>FN</td>
<td>TN</td>
</tr>
</tbody>
</table>

4.3. Area metrics

With the help of Table 1, subsequent tables are constructed with a similarity index (SI), misclassification rate, and correct boundary rate as three types of metrics that are sufficient to reflect the algorithms’ performance well. Misclassified tissue rate is calculated by dividing nonoverlapping areas by total brain surface area, which is \( \frac{(FP + FN)}{(FN + FP + TP + TN)} \). Accuracy is just the misclassification rate subtracted from unity. SI is defined as in Eq. (4):

\[
\frac{2 \times |M_1| \cap |M_2|}{|M_1| + |M_2|} \tag{4}
\]

where \( M_1 \) is the area produced by the algorithm and \( M_2 \) is the area marked by the expert.
4.4. Boundary metrics

Pixels of boundaries found automatically are overlapped with manually labeled pixels revealing the correct boundary percentage. For this metric to be calculated, the Euclidean distance between two boundaries is measured. The adjacency threshold (overlapping criterion) is set to diagonal length of 1.41 pixels. Moreover, distances between two boundaries are calculated, which leads to standard deviations and confidence intervals.
4.5. Validation of common data
The FSGPC is compared with SPM by running both algorithms on the same images of BrainWeb where the GM-WM boundary is a priori known. Since SPM is already compared to packages like FSL and ITK for other common databases, FSGPC versus SPM will also give an opinion about where FSGPC stands among the prevailing algorithms.

5. Results and discussion
For evaluating the algorithms, 7 axial slices from each patient are chosen and tested. The chosen slices have similar ordering as the 11th, 12th, 13th, and 14th in head-to-feet direction. The same slices will reflect the same matched patterns so that a fair comparison can take place, as visualized in Figure 7.

![Figure 7. Slices 11, 12, 13, and 14 in each row belonging to a single patient. Visualization of patchy GM-WM boundaries.](image)

5.1. Quantitative elucidation of contours’ cooperation
A sample of how quantitative evaluation is done on boundary cooperation is displayed for 2 patients, each with four slices, in Table 2. Points of the GM-WM interface that were detected with FSGPC-I are given in Table 2 according to contributing geodesics that they belong to. Each geodesic has two columns, one for the total number of its points and the other for chosen points it gives to GM-WM border.

5.2. Visualization of the contours’ cooperation
A good strategy in displaying the results is coloring a geodesic always with the same color throughout the images. This strategy is not only better to see the cooperation of geodesics but makes the image intensity change along the coastal band as well. The colors used for intensity levels are given in Table 3.
Table 2. Points of different geodesics for construction of GM-WM boundary by FSGPC-I.

<table>
<thead>
<tr>
<th>Geodesic 60</th>
<th>Geodesic 68</th>
<th>Geodesic 76</th>
<th>Geodesic 84</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total points</td>
<td>Used Total points</td>
<td>Used Total points</td>
<td>Used Total points</td>
</tr>
<tr>
<td>Patient 1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Slice 11</td>
<td>2554</td>
<td>1893</td>
<td>4386</td>
</tr>
<tr>
<td>Slice 12</td>
<td>1624</td>
<td>874</td>
<td>4267</td>
</tr>
<tr>
<td>Slice 13</td>
<td>2884</td>
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<td>Slice 14</td>
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<tr>
<td>Slice 14</td>
<td>4730</td>
<td>3872</td>
<td>4544</td>
</tr>
</tbody>
</table>

Table 3. Geodesic contours’ intensities and colors denoting them.

<table>
<thead>
<tr>
<th>Level sets</th>
<th>Color</th>
</tr>
</thead>
<tbody>
<tr>
<td>60</td>
<td>Yellow</td>
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<tr>
<td>68</td>
<td>Red</td>
</tr>
<tr>
<td>76</td>
<td>Green</td>
</tr>
<tr>
<td>84</td>
<td>Magenta</td>
</tr>
<tr>
<td>92</td>
<td>White</td>
</tr>
<tr>
<td>CSF-GM</td>
<td>Thickened</td>
</tr>
<tr>
<td>Cavities</td>
<td>Cyan</td>
</tr>
</tbody>
</table>

GM-WM interfaces extracted by FSGPC-I are given in Figure 7. The number of displayed slices is kept small for not extending the paper-size but is enough for revealing the cooperation of different geodesics. Figure 8 displays a closer look at some regions of slices in Figure 7 with CSF-GM borders mounted on.

![Figure 8](image_url)

**Figure 8.** Closer look at some regions of slices in Figure 7. (a) and (b) from 12th and 13th slices of Patient 1 in first row of Figure 7. (c) Zoomed in version of yellow ROI in 13th slice of Patient 3 in 3rd row of Figure 7. (d) ROI from 13th slice of Patient 1. Mounted CSF-GM boundaries as blue contours.

Extracted GM-WM interfaces by FSGPC-II are given in Figure 9. Green ROIs are zoomed in on to emphasize how the algorithm tunes into the cavities. The rectangular area in Figure 9a is zoomed in on in Figure 9b, where the red boxes attract attention to the junctions between the geodesics. Thus, the same ROIs are segmented in Figures 8 and 9b, supplying a comparison between FSGPC-I and -II. FSGPC-II is better with its property of cavity recovery. Figure 9 also displays the final appearance of the GM-WM interface, including nearly perfect solutions at cavities.
Experts visually evaluated the resulting segmentations by GM-WM extraction on 50 MRI slices from 20 different patients, which is summarized in Table 4.

Table 4. Visual evaluation of segmented output images by 2 experts.

<table>
<thead>
<tr>
<th></th>
<th>Good</th>
<th>Reasonable</th>
<th>Poor</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OE</td>
<td>KM</td>
<td>OE</td>
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<tr>
<td>FSGPC-II</td>
<td>133</td>
<td>130</td>
<td>5</td>
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<tr>
<td>FSGPC-I</td>
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</tbody>
</table>

5.3. Discussion of the geodesics’ cooperation

It can be seen in the results above that many geodesics cooperate for the interface. Visualization gives confidence about the strength of FSGPC. Moreover, it can be seen that both FSGPC-I and -II use the same colors for GM-WM, revealing that the same geodesics are chosen by both algorithms. Thus, the algorithms are consistent. The results also prove the intra-slice inhomogeneity. Otherwise, the same color would be seen on a single slice.

The results of FSGPC-I in Figure 7 prove inter-slice (intra-patient) intensity differences by showing the sliding of colors from yellow to magenta. In the first row of Figure 7, yellow is becoming less while purple is becoming more widespread while going from the leftmost image to the rightmost one of Patient 1. The same is also true for Patient 3. The inter-patient intensity difference is obvious by looking at the color changes between the rows. Inter-slice and inter-patients color slides were expected, of course. Colors denoting higher geodesics are seen for Patient 3. However, the algorithm does its best again.

The yellow square box that is extracted from the 14th slice of Patient 3 in Figure 7 is zoomed in on and shown in Figure 8 for a better impression. Moreover, the lateral ventricle in the 13th slice of Patient 1 in Figure 7 shows the cooperation very well. It consists of 3 different colors denoting 3 geodesics. It is zoomed in on and shown again in Figure 8.

Comparison of FSGPC-I and -II can be done with Figure 9, which is produced by FSGPC-II. The first difference between the two algorithms is the addition of more cavities by FSGPC-II, which can be seen in Figure 9c within two green rectangular boxes. The superiority of FSGPC-II is obvious when cyan-colored cavities are observed in Figure 9b and Figure 8, which are extracted by the algorithms FSGPC-I and FSGPC-II, respectively, where the same ROI is zoomed in on.

The patchy GM-WM boundary is a result of geodesics’ cooperation but is easily converted to a seamless continuous closed curve by close junctions at open ends of segments from different geodesics as in Figure 9d.
5.4. Comparison with experts

After filling in a comparison table (Table 2), the evaluation metrics are obtained. These metrics are written for a single patient in Table 5. The last row has the total average of metrics for all patients.

Table 5. Comparison with ground truth (by experts).

<table>
<thead>
<tr>
<th></th>
<th>Misclassified tissue (%)</th>
<th>Similarity index</th>
<th>Correct boundary (%)</th>
<th>Processing time</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Expert 1</td>
<td>Expert 2</td>
<td>Expert 1</td>
<td>Expert 2</td>
</tr>
<tr>
<td></td>
<td>KM</td>
<td>OE</td>
<td>KM</td>
<td>OE</td>
</tr>
<tr>
<td>FSGPC-I</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Patient 1</td>
<td>Slice 14</td>
<td>6.4</td>
<td>8.5</td>
<td>0.89</td>
</tr>
<tr>
<td></td>
<td>Slice 13</td>
<td>6.1</td>
<td>9</td>
<td>0.89</td>
</tr>
<tr>
<td></td>
<td>Slice 12</td>
<td>7</td>
<td>6.5</td>
<td>0.88</td>
</tr>
<tr>
<td>FSGPC-II</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Patient 1</td>
<td>Slice 14</td>
<td>4.5</td>
<td>6</td>
<td>0.95</td>
</tr>
<tr>
<td></td>
<td>Slice 13</td>
<td>5</td>
<td>8</td>
<td>0.92</td>
</tr>
<tr>
<td></td>
<td>Slice 12</td>
<td>5</td>
<td>8.1</td>
<td>0.92</td>
</tr>
<tr>
<td>Exp 2 (OE)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Patient 1</td>
<td>Slice 14</td>
<td>6</td>
<td>9</td>
<td>0.92</td>
</tr>
<tr>
<td></td>
<td>Slice 13</td>
<td>5.5</td>
<td>5.5</td>
<td>0.94</td>
</tr>
<tr>
<td></td>
<td>Slice 12</td>
<td>4.5</td>
<td>4.5</td>
<td>0.96</td>
</tr>
<tr>
<td>AVERAGE ALG 1</td>
<td></td>
<td>6</td>
<td>8</td>
<td>0.89</td>
</tr>
<tr>
<td>AVERAGE ALG 2</td>
<td></td>
<td>4.8</td>
<td>7.7</td>
<td>0.93</td>
</tr>
<tr>
<td>AVERAGE Exp 2</td>
<td></td>
<td>5.7</td>
<td></td>
<td>0.91</td>
</tr>
</tbody>
</table>

5.5. Discussion of comparison with experts

The true classification rate of WM is 4.8% for FSGPC-II and the similarity index is 91%, as given in Table 5. This is a promising result when compared to other SI values in [6,11,12]. They are somewhere between 76% and 92% for the segmentation of WM. Average overlap metrics (AOMs) by Yu et al. [4] are 80% and 84% for GM and WM tissues, respectively. The same AOMs by Liao et al. [21] are 85% and 86%. De Boer et al. [18] recently reached a highest SI for WM, which was 92%, by using atlas knowledge as a priori information. FSGPC-II has AOMs of 93% and degree of equality of 88% for WM, which is better than that research, although no a priori information is utilized.

Angelini et al. [22] gave a best minimum error rate of 13.5% while comparing many algorithms. FSGPC-II favors this research by achieving a misclassification rate of 4.8% and 7.7% as evaluated by different experts. However, it must be remembered that studies were tested on different data and only the resulting scores are compared.

Thus, comparison with experts’ drawings will be more valuable. There is an inter-user dependence on the drawings of experts and the similarity between them is 91%. It can be deduced that FSGPC-II can be accepted as a third expert since its SI with experts is 93%, and for FSGPC-I, it is 89%. Segmentation accuracy of WM according to FSGPC-II is 95.2% and that again favors the accuracy noted by Cuadra et al. [11], which is 85%.

When the boundary is of concern, few algorithms are attempted for evaluation of their results since an exact coincidence with the true boundary is difficult. Compared to these few algorithms revealing a border, FSGPC-II reaches an accuracy of 77% (Table 6). A much easier case of brain extraction by the McStrip algorithm by Boesen et al. [18] has 65.7% border accuracy.

The standard deviation, $\sigma$, is calculated as only 1.01 pixels for differences between FSGPC-II and Expert 1. That measure is 1.14 between experts. When the adjacency criterion is loosened and taken as 3.2 pixels, the correct boundary rate rises to 96% for FSGPC-II, justifying the claim that FSGPC-II traces the border just like a human.
Table 6. Distance of found interface by FSGPC-II [15] from manually drawn interface.

<table>
<thead>
<tr>
<th></th>
<th>Mean $\mu$</th>
<th>Std.dev. $\sigma$</th>
<th>Correct Boundary dist $&lt; \sqrt{2}=1.41$</th>
<th>dist $&lt; 2$</th>
<th>dist $&lt; 3.2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alg 2 vs Exp 1</td>
<td>1.5</td>
<td>1.74</td>
<td>65%</td>
<td>72%</td>
<td>90%</td>
</tr>
<tr>
<td>Alg 2 vs Exp 2</td>
<td>1.06</td>
<td>1.01</td>
<td>77%</td>
<td>85%</td>
<td>95%</td>
</tr>
<tr>
<td>Exp 1 vs Exp 2</td>
<td>1.14</td>
<td>1.56</td>
<td>77%</td>
<td>82%</td>
<td>94%</td>
</tr>
</tbody>
</table>

When the processing time is of concern, it is found to be at an acceptable level. Speeds in the literature vary between 5 min and 30 min (for the skull) since some algorithms need the whole brain volume for aligning it to a standard reference. If only a few slices are of concern, this is a waste of time. However, 25 s is enough for geodesics to apply for a single slice. Thus, having no manual intervention and skipping the aligning step or supervisory training, FSGPC is certainly faster.

5.6. FSGPC-II vs. SPM on common synthetic BrainWeb data

BrainWeb produces synthetic images with an attached ground truth. Noise levels and inhomogeneity amount can be adjusted. Both SPM8 and FSGPC-II are run in the MATLAB environment.

Having the property of fine-tuning at cavities, FSGPC outperforms SPM8, especially in regions that are defected by noise and inhomogeneity. It can be seen better in Figures 10a and 10b. Yellow ROIs involve a pattern like fingers. FSGPC works well and the final boundary pattern is caught easily, as in Figure 10c, whereas SPM8 lacks these cavities. The same is true for other encircled regions.

Figure 10. Comparison of SPM and FSGPC-II. Synthetic image in (b) from BrainWeb with three yellow ROIs. Ground-truth image in (d). (a) Output of SPM8. (c) Output of FSGPC-II with finger-like structure in ellipsis.

FSGPC has average SI value 6% better than SPM8, reaching 96%. Other packages are known to have lower performance when compared to SPM [23,24] based on the same data.

For the noisy images with inhomogeneity and Gaussian white noise, FSGPC outperformed SPM again. These tests were tried with up to 5% noise and 40% inhomogeneity as supplied by the BrainWeb database with ground truth volumes. As seen in Figure 11 in the second row, by just two geodesics, our algorithm catches the boundaries where SPM gives no sharp interface between gray and white matters.
There are, however, some shortcomings of the technique. It is apparent that FSGPC only extracts cortical tissues and is not interested much in subcortical ones. Thus, only sulci and gyri areas are of concern where atrophy evidently takes place. For the subcortical case, algorithms seem effective but refinements must be done. Moreover, the brain extraction (a stripped skull) is obligatory before the application so that geodesics will not get confused with nonbrain long counters.

6. Conclusion
An automatic extraction of the GM-WM boundary exploiting the spatial information by geodesics is put forward. Adapting the problem well, geodesics imitate human perceptual edge sensitiveness and helps in combining the edge segments of the boundary as a continuous close curve.

Since the system utilizes the cooperation of succeeding intensity levels, it is not affected much by two basic noise causes of PV and inhomogeneity. Moreover, the proposed system can work on both T1w and rarely used T2w MRIs as a plus to existing techniques, which work basically on T1w. The technique can easily be adapted to 3D segmentation of GM where the geodesics will then be isosurfaces passing from voxels with the same intensity values as seen in Figure 12. The PV effect will then be minimized, thus producing a higher accuracy.
Figure 12. An example of GM-WM boundary extraction in 3D. Tests continue to lower time duration. Geodesic cooperation is replaced by isolevel surfaces' cooperation.

With the high precision obtained by FSGPC, one can monitor the atrophy better by more reliable quantitative measures [25]. The accuracy of the method is so close to experts' agreement that it traces nearly the same boundary that they draw. Finally, it is proven to be an effective novel technique for the segmentation of cortical brain tissues with the elegant features of being unsupervised, fully automatic, and fast.

References


