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Effective Brain Contour Segmentation based on Active Contour Model

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Abstract

Object recognition is usually processed based on region segmentation algorithm. This paper suggests effective region segmentation method based on R2-map within the magnetic resonance (MR) theory. When we do pre-processing, proposed method was composed of R2-map process. And then we do the Gray-white matter segmentation by Active Contour Model(ACM) in post-processing. In this study, the experiment had been conducted using images including the brain region and by getting up contrast enhancement image of R2-map for segmentation to extract region (white matter) segmentation even when the border line was not clear. As a result, an average area difference of 5.8%, which was higher than the accuracy of conventional region segmentation algorithm, was obtained.

Keywords: R2-map, Brain Segmentation, MR theory, Active Contour Model, Curve Fitting

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1. Introduction

Object recognition is a very important part of image processing. It can begin with area segmentation and image segmentation, which is crucial for image interpretation and is an indispensable stage of image processing. Various image segmentation methods have different characteristics and perform differently according to the input image characteristics; but despite these differences, their image segmentation problems have the same causes. According to the distribution of neighboring pixel values, non-segmentation or excessive segmentation occur. These problems are common chronic problems with various image segmentation methods, and many studies have been conducted to resolve them.

Generally, image segmentation algorithms include the threshold value technique, the edge detection technique, region growing, and the technique of using texture characteristic values [1-4]. The threshold value method involves creating histograms for the given image, determining the critical value, and partitioning the image into the object and the background. Edge detection refers to the process of looking for gray-level discontinuous pixels in an image. Region growing [5] was designed to measure similarities between pixels to be able to expand and segment an area. In addition, the statistical method and the structural method use texture characteristic values that quantify discontinuous changes in pixel values in an image [6]. In addition to these general methods, methods of segmenting an area manually have been extensively studied, and multi-area segmentation methods are being applied [7]. Of these methods, the Graph Cut [8] method and the GrabCut [9] method of looking for borders to minimize energy have been proposed as methods of minimizing the involvement of users, but they have the disadvantage of requiring the setting of the initial area. Also, the Region Adaptive Algorithm method of extracting features by area using appropriate methods has been proposed, but it has the weakness of yielding inaccurate results in ambiguous borders. To resolve these shortcomings, the curve fitting method based on regional minimum values is being used. In addition, ACM or the snake method [10] was proposed to converge to the point where the energy value is minimum, to detect the optimal contour line. This snake method requires significant user information involvement, however, and has the problem of the misconception of the energy value in a shady area as a different area. To resolve these problems, diverse snake methods have been proposed [11-12].

Representative image segmentation algorithm stems from the difference in pixel information. The difference in pixel, which is input information, is determined by the difference in brightness or shape/pattern, which is connecting information. However, if the difference cannot be identified from the input information, the accuracy of region segmentation dramatically decreases. This paper suggests an effective segmentation method using magnetic resonance (MR) theory to resolve this problem. Magnetic resonance imaging (MRI) is an examination method that produces images using nuclear magnetic resonance (NMR). Resonance means an amplification reaction to the stimulations having with the same frequencies. NMR method measures the signals that come out from a nucleus when it is stimulated by its own characteristic frequency. Human bodies become feeble magnets in a magnetic field. Because the degree of magnetization differs according to the tissues of a human body, an MRI image can be obtained by measuring and graphing the difference through computer processing [13].

There are three types of MRI images: proton density image, T1 image, and T2 image [14-15]. This paper worked towards improving the quality of an image including the brain region, and tried to isolate the brain region (white matter) from the image using texture analysis method by setting up several region of the brain image. In MR image, the methods are used to distinguish differences from normal tissues through factors such as spinlattice, T1, spin-spin, T2, relaxation times, etc. In this paper, T2-based sequence is used; experimental data are MR images of rats; and R2-map value is obtained by calculating T2-map. By taking the reciprocal of the calculated T2-map (1/T2), R2-map can be calculated. In general, T2 value appears to differ depending on the iron (Fe) content of the tissue. Although individual differences somewhat exist, generally T2 values in the tissues containing a large amount of the iron component are yield relatively lower than other signals and noises.

In this paper, we try to enhance the accuracy of object segmentation by using R2-map process and improved Snake model in ACM. Generally, segmentation methods require post-processing to improve their accuracy. If the first detection work can minimize errors, however, low-cost post-processing alone can yield effective results. Thus, the post-processing method is improved to focus on the initial snake point allotment, convergence of contour lines, and correction work, and to minimize the post-processing costs of area segmentation algorithms.

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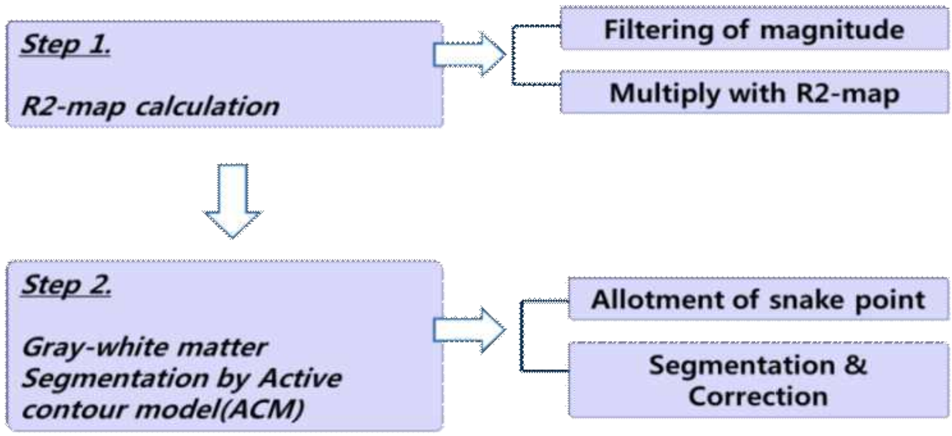
2. Proposed method

In applying the object recognition algorithm, input image characteristics are important. Considering the recognition algorithm's input parameter value, it is assumed that the input image's pre-processing result is the same. Recognizing the brain region (white matter) in an MR image provides important information for deciding on therapy or operation method, as well as identifies diseases in the brain. This paper tries to enhance the accuracy of recognition by using R2-map information and improved Snake model. The proposed method works as follows: First, the R2-map process in T2 image is calculated; second, the calculated each brain regions by the improved snake model. Figure 1 shows the general algorithm flowchart. Detailed and step-by-step explanation will be given thereafter.



[Fig. 1] Overview of the proposed method

2.1. Calculation of R2-map

In MR image, the methods are used to distinguish differences from normal tissues through factors such as spinlattice, T1, spin-spin, T2, relaxation times, etc. In this paper, T2-based sequence is used; experimental data are MR images of rats; and R2-map value is obtained by calculating T2-map. Images are acquired using FSE (Fast Spin Echo) sequence, and to calculate T2-map, like the formula (1), Signal Intensity (SI) is calculated [14].

$$SI = SI_0(\exp(-T_E / T_2) \quad (1)$$

The scan parameters utilized for T2-map calculation were TR / TE: 3 000 / 30 ms, NE (number of echo): 8, and slices: 24, and the resolution was set to 280 x 280. Employing the parameters, T2-map was calculated by the following formular (2) [15,16].

$$T_2 = -\frac{T_E}{\ln\left(\frac{SI(T2W)}{SI(PD)}\right)} \quad (2)$$

By taking the reciprocal of the calculated T2-map (1/T2), R2-map can be calculated. In general, T2 value appears to differ depending on the iron (Fe) content of the tissue. Although individual differences somewhat exist, generally T2 values in the tissues containing a large amount of the iron component are yield relatively lower than other signals and noises. Therefore, conversely R2 values are evenly distributed with significantly high values. This paper suggests a R2-map information-based method as most meaningful feature information for comparison of similarity.

2.2 Fitting by Grid-fit method

In order to perform the fitting operation while maintaining the uniformity of calculated R2-map, this paper uses the method applying a least-square fit for each grid of the image, and it was expressed in the name of grid-fit. We assume that the phase data is spatially smooth and use a Grid-fit method. We propose a more robust and simple phase unwrapping method. The key to our method is to begin the iteration at each grid with least-square fitting by using MiP (Median intensity Projection) process at each axis pixels. Our scheme as the Grid-fit method described in Fig. 2. The steps on the proposed Grid-fit method are:

1.	Compute phase image in MR T2 scan raw data.
2.	Divide by KxK Grid-regions, that Grid-region size can changeable depend on phase image resolution. Sample Grid-region size K is 6.
3.	Compute MiP value at each axis pixels.
4.	Adjust the Least-square fitting by using MiP values.
5.	Fill median value in each pixel by fitted values at local grid.
6.	After fit the local grid, adjust the gaussian filtering at entire Grid-region to enhance the global inhomogeneity.

[Fig. 2] Processing of Proposed Grid-fit

In this processing method, the basis of the grid region was set to 6X6, and a least-square polynomial expression was solved using a cubic equation. It was treated with a cubic equation to remove spike impulsive noise as well as to have the direction of the minimal intensity.

And for the entered values used in the least-square method, the median values of x and y axis in the local grid region were projected, and a representative value for each axis was obtained. Additionally, through the result value of least-square fitting adjusted to each x and y axis, the median value of two values matched to each x and y axis was put as the adjusted local grid-fit result value. In the same way, each grid region is calibrated, and to finally adjust the entire image, the task for mitigating non-uniformity is performed through the Gaussian filter.

Finally, in the improved image generation method, an optimized image is generated by the product of the previously calculated R2-map and the magnitude image.

2.3. Gray-white matter Segmentation by ACM

In this phase, the contrast quality of above enhancement result, which have previously been calculated. The candidate boundary line should be using as segmentation boundary in the next step, which uses improved Snake method. Detecting boundary line consists of two tasks. First is limiting the scope of detection. This requires establishing a candidate area to detect boundary line, within which the actual brain region should be detected. Second is identifying the pixels that are considered meaningful as feature points. These feature points are calculated as subtract between original magnitude image and R2-map processed magnitude image. And in order to allot the Snake points on boundary line, we use a Mean-shift clustering[17]. Then we used improved Snake method by using this allotted Snake points.

2.3.1. Allotment of Snake points

These feature points are calculated as subtract between original magnitude image and R2-map processed magnitude image. And in order to allot the Snake points on boundary line, we use a Mean-shift clustering. Mean-shift is a procedure for locating the maxima of a density function given discrete data sampled from that function. It is useful for detecting the modes of this density. This is an iterative method, and we start with an initial estimate x. Let a kernel function K(xi, x) be given. This function determines the weight of nearby points for re-estimation of the mean. Typically we use the Gaussian kernel on the distance to the current estimate, The weighted mean of the density in the window determined by K.

$$m(x) = \frac{\sum_{xi \in N(x)} K(xi - x)xi}{\sum_{xi \in N(x)} K(xi - x)} \tag{4}$$

where N(x) is the neighborhood of x, a set of points for which k(x) is not 0. The mean-shift algorithm now sets x: m(x), and repeats the estimation until m(x) converges. And we used improved Snake method by using this allotted Snake points.

2.3.2. White matter segmentation by improved Snake model

In order to extract the white matter, we use Greedy snake method[18] which performed using the information on the previously calculated Snake points. By concept of Greedy snake method, the energy function $E_{snake}(v_i)$, which moves snake points in a 2D image with the minimum energy value,

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is expressed as the sum of the internal energy (i.e., the continuity), the curvature energy term, and the external energy term, as shown in the following equation 5.

$$E_{snake}(v_j) = \sum_{i=0}^{N-1}[\alpha \cdot E_{continuity}(v_{i,j}) + \beta \cdot E_{curvature}(v_{i,j}) + \gamma \cdot E_{external}(v_{i,j})] \tag{5}$$

If $v_{i,j} = (x_{i,j}, y_{i,j})$ and i = 0; ...N-1, denoting the total number of snake points, and $x_{i,j}$, $y_{i,j}$ are the x, y coordinates of the i-th snake point of the j-th repetition. The continuous energy minimized the distanced between the snake points obtained at the j+1st repetition to the average distance $\overline{d_j}$ between the snake points at the previous j-th repetition, thereby eventually equalizing the distance between N number of snake points. This snake method considers and converges on only a particular area with a 1x3 mask, on the basis of the allotted snake points.

Thereafter, the continuous energy is expressed as in Equation 6, and $\overline{d_j}$ is calculated as shown in Equation 7.

$$E_{continuity}(v_{i,j}) = |\overline{d_j} - \| v_{i,j} - v_{i-1,j+1} \|| \tag{6}$$

$$\overline{d_j} = \frac{1}{N}\sum_{i=0}^{N-1} \| v_{i+1,j} - v_{i,j} \| \tag{7}$$

Equation 6 is subject to the condition $v_{0,j} = v_{N,j}$. in which | | is the scalar absolute value and || || is the vector length (Norm). The external energy is generated by various image characteristics such as lines and edges. Generally, energy is used, and a small value is taken in a place with a significant gradient, thereby positioning a snake point on the contour of the relevant object. The external energy is calculated using Equation 8.

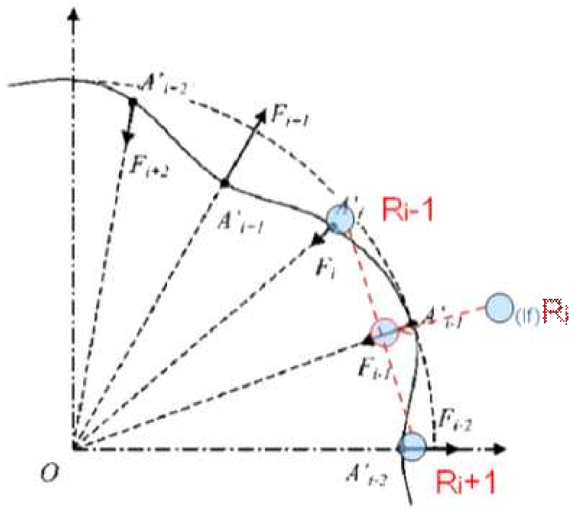
$$E_{external}(v_{i,j}) = -|\nabla f(v_{i,j})|^2 \tag{8}$$

In the aforementioned expression, ∇ denotes the gradient, and the energy term's parameters, α, β, γ, are weighted, thereby determining the importance of the internal and external energy terms.

The correction method for the snake convergence results begins with the middle point of the initial area set by the user. The contour line correction can be assessed using the following Equation 9.

$$E_{tmp} = \sum_{i=1}^{n} \left| \frac{R_{i-1} + R_{i+1}}{2} - R_i \right| \tag{9}$$

When the allotted snake points are assumed to be in the order of Ri-1, Ri, and Ri+1, the distance between the middle point of the initially set area and each snake point is calculated. If the relevant Ri distance is greater than the average distance of Ri-1 and Ri+1, as in the preceding equation, it is considered problematic. Likewise, the Ri point is corrected using the linear interpolation of Ri-1 and Ri+1. This interpolation is meant to reduce the post-treatment work, since when conducting contour line convergence work as mentioned, three units of snake point convergence work are processed simultaneously. This is shown in Figure 3.



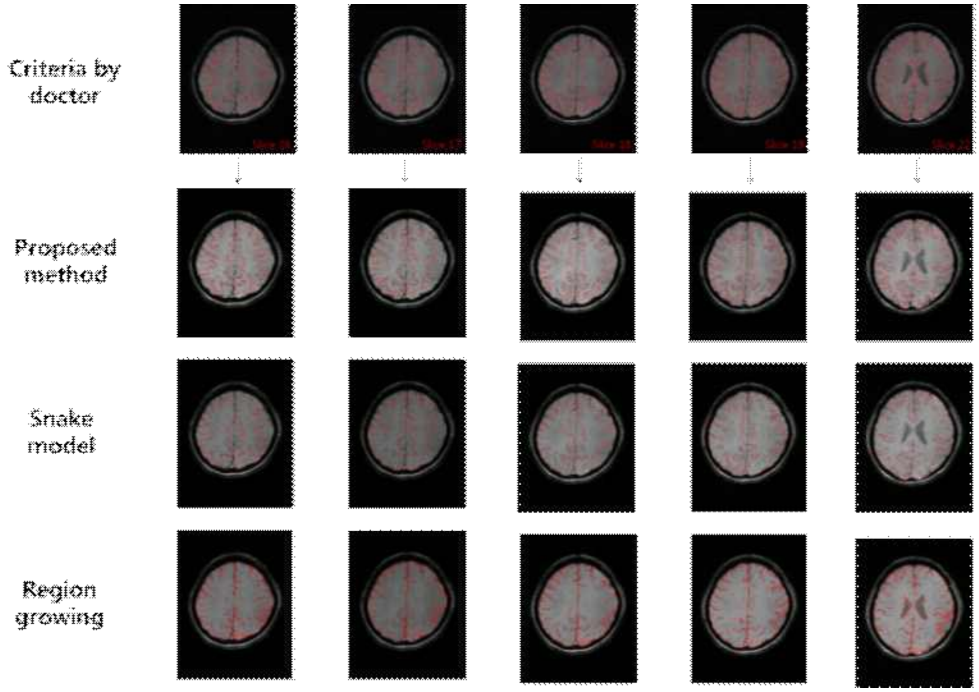
[Fig. 3] Correction by linear interpolation

3. Experiment

To evaluate the proposed method, experiments based on medical MR imaging were performed, and the results were compared with the reference image achieved by a specialist doctor. Thus, the accuracy of the method was evaluated quantitatively. Towards this end, the difference ratio between the reference image and the area from the proposed method was calculated, and can be expressed by the following Equation10.

$$R_{diff} = \frac{|R_{criteria} - R_{proposed}|}{R_{criteria}} \times 100 \qquad (10)$$

In Equation 10, R_{diff} denotes the area difference ratio, $R_{criteria}$ denotes the area of the reference image, and $R_{proposed}$ represents the area created by the proposed method. For this experiment, a total of 60 MR images were processed, and the relevant image criteria were evaluated according to the results of the proposed method and of Equation 10, after a specialist doctor established the baseline using Adobe Photoshop CS. In our case, to evaluate the accuracy, we calculate the average area difference by each slice in brain volume data. As a result, an average area difference ratio of 5.8% was determined. Figure 8 shows the some samples of evaluation result in the proposed method.



[Fig. 4] The comparison samples of each final results

To provide more points for comparison, other techniques were implemented such as the general region growing [5] and Snake method[10] using the slice 60 images in Figure 8 and Table 1 show the sample results of the application of the comparison algorithm.

Actually, proposed method is composed of general segmentation algorithm in addition to MR theory as R2-map information. So that's why we choose the comparison method like a region growing and snake model. In case of region growing, seed point is set the manually by criteria boundary. Threshold value was calculated by average intensity. In case of snake model, initial contour set the manually by criteria boundary. According to the results shown in Figure 8 and Table 1, the existing snake method and region growing caused some problems in that the intensity or energy recognized portions with ambiguous shades as different areas.

[Table 1] Results of comparison of the proposed method with the other methods

Method	Average area difference ratio
Region Growing	12.5%
Snake	10.2%
Proposed Method	5.8%

4. Conclusion

In this paper, R2-map process within the MR theory has been used to resolve the basic limitations in computer processing. It suggested detection of meaningful segmented regions. It also suggested an effective algorithm to detect the brain region using improved Snake model based on R2-map image. This method did not stick to fundamental brightness processing, but focused on finding the region that adjust the enhance contrast by R2-map processing, considering the functional characteristics of the susceptibility. The results have confirmed that the meaningful region, which have been detected through a corresponding susceptibility, that is, the method in which the brain region detected through R2-map were used was more accurate than the conventional one in which the difference of pixel information was used. However, when the R2-map result has considerable noise or has been distorted from the internal region in brain, the accuracy of detection becomes low. This limitation should be complemented by further research on image improvement. This paper aimed to verify the possibility of improvement in computer processing by adopting the MR theory. Further research needs to be conducted to help in resolving the general limitations through the appropriate combination of MR theory and computer science.

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