# Segmentation of Head MR Images Using Hybrid Neural Networks of Unsupervised Learning

Toshimitsu Otani, Kazuhito Sato, Member, IEEE, Hirokazu Madokoro, Member, IEEE, and Atsushi Inugami

***Abstract*— This paper presents an unsupervised segmentation method using hybridized Self-Organizing Maps (SOMs) and Fuzzy Adaptive Resonance Theory (ART) based only on the brightness distribution and characteristics of head MR images. We specifically examine the features of mapping while maintaining topological relations of weights with SOMs and while integrating a suitable number of categories with Fuzzy ART. Our method can extract intracranial regions using Level Set Methods (LSMs) of deformable models from head MR images. For the extracted intracranial regions, our method segments brain tissues with high granularity using SOMs. Subsequently, these regions are integrated with Fuzzy ART while maintaining relations of anatomical structures of brain tissues and the order of brightness on T2-weighted images. We applied our method to head MR images that are used at clinical sites. We obtained effective and objective segmentation results according to the anatomical structural information of the brain for supporting diagnosis of brain atrophy. Moreover, we applied our method to a head MR image database including data of 30 men and women in their 30s–70s. Results revealed a significant correlation between aging and expanding of cerebrospinal fluid (CSF).**

## I. Introduction

High-resolution medical images have been used at clinical sites with great recent progress in their respective modalities. These medical images are used now not only for diagnosis, but also for data sharing via electronic medical records and dialogues for informed consent. Confronted with the need for integrating these systems, it is desired from the viewpoint of improved diagnostic accuracy and reduction of the load to create an object according to the target tissue rather than direct use of images. Therefore, a method to segment brain tissues for diagnosis using head MR images for objective diagnosis is necessary. Moreover, the method should not be influenced by the operator's subjective assessment. However, segmentation of brain tissues is regarded adversely because boundaries of brain tissues are obscure. Brain tissues are classifiable into grey matter (GM) comprising neurons, and white matter (WM) comprising axons. Brain atrophy is caused by decreasing GM, which is not always accompanied by decreased WM. Moreover, cerebrospinal fluid (CSF), which flows to the region of brain atrophy, expands according to the progress of brain atrophy. For diagnosis of the brain atrophy, diagnosticians concentrate their attention on CSF, which is easily observed visually. Although various methods have been proposed for segmentation of head MR images, they diagnose brain atrophy empirically and subjectively based on the appearance of original images. For that reason, objective segmentation methods are necessary for supporting and reducing the load of diagnosis.

Various methods have been proposed for segmentation of head MR images [1]–[6]. These methods are classifiable into two approaches: those which require representative points selected by an operator and those which do not. The approach must specify representative points for each tissue to be segmented. Segmentation results depend strongly on the subjective judgments of an operator, although the accuracy is superior. Moreover, these methods require representative points for segmentation of head MR images. These requirements heavily burden the operator. Especially, generalization ability is lowered and the network responds only for training data for neural network based methods if the number of representative points set by the operator is smaller. On the other hand, segmentation without the necessity of specification of representative points is attracting attention from many investigators. Madokoro et al. proposed an unsupervised segmentation method used in self-mapping characteristics of one-dimensional Self-Organizing Maps (SOMs) based only on the brightness distribution and characteristics [7]. In their method, the mapping (Kohonen) layer of SOMs is set to five units. The correspondence relation between brain tissues and segmentation results differs among MR images. At clinical sites, T2-weighted images are used most frequently. Edema and tumors are shown with high brightness in T2-weighted images. However, we cannot divide GM and WM because the T2-weighted images have only a slight difference in their brightness. Therefore, when the mapping layer of SOMs is greater than six units, their method requires an assignment tissue while confirming the correspondence relation with tissues by an operator. Brightness distribution of MR images varies among individuals. It is important to use the unsupervised segmentation framework of brain tissue without influence by the operator's subjective interference.

This paper presents an unsupervised segmentation method of brain tissues on head MR images to quantify the degree of the brain atrophy with a view to reducing the load on the diagnostician. We use axial head MR images, for which it is easy to confirm a frontal lobe with notable brain atrophy. The modality that is used in the evaluation of the brain atrophy is T2, especially in brain dock examinations at clinical sites. Moreover, the T2-weighted images readily portray CSF,

Toshimitsu Otani, Kazuhito Sato, and Hirokazu Madokoro are with the Faculty of Systems Science and Technology, Akita Prefectural University, 84-4 Aza Ebinokuchi Tsuchiya, Yurihonjo City, 015-0055, Japan (phone: +81 184 272081; fax: +81 184 272180; email: m11a004@akita-pu.ac.jp), Atushi Inugami is with Akita Kumiai General Hospital, 273-1, Nishibukuro, Iijima, Akita 011-0948, Japan.

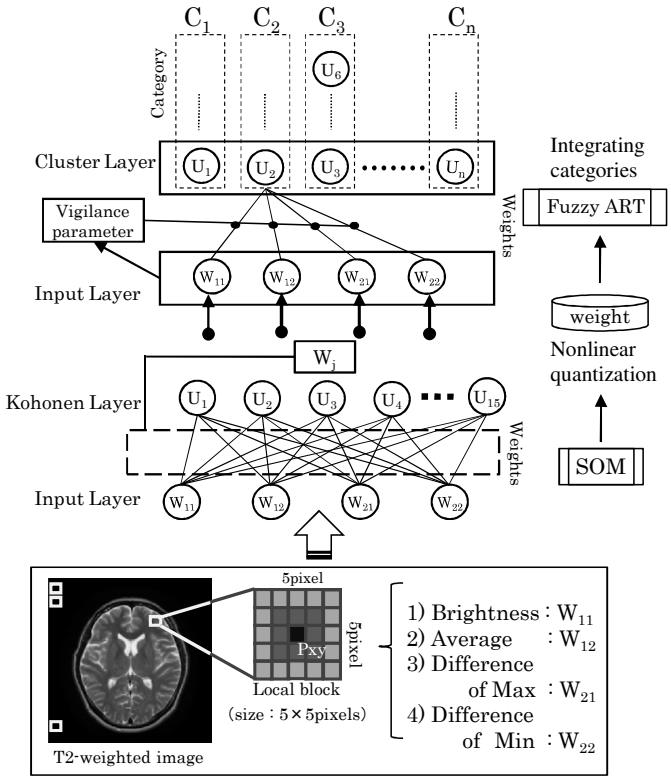


Fig. 1. Network architecture and the entire procedure used for our method.

which is depicted with higher brightness than other modality images. On the histogram of T2-weighted images, GM and WM are located respectively in the high and low brightness range.

We use SOMs for classification of categories that are mapped brightness characteristics of brain tissues. Subsequently, we use Fuzzy Adaptive Resonance Theory (ART), which maintains the neighborhood regions and integrates categories according to the order of the brightness distribution. We applied our method to clinical head MR images of 30 men and women in their 30s–70s and obtained results according to the anatomical structural information of the brain. From visual evaluation by a diagnostician, the segmentation results are fitted to quantification for brain atrophy as a diagnosis support. Moreover, we applied our method to an MR image database comprising clinical head MR images. Results reveal a significant correlation between aging and expansion of CSF.

## II. Proposed Method

The determination of tissue boundaries is a challenging task because the brightness characteristic is not clearly apparent on a brightness histogram. For this study, we hybridize SOMs and Fuzzy ART for segmentation of brain tissue based only on the brightness characteristics and distribution of head MR images. We specifically examine the mapping function while maintaining topological relations of weights on SOMs and integrating a suitable number of categories on Fuzzy ART. Our method, used in unsupervised learning of SOMs and Fuzzy ART, requires no feature points that are selected subjectively by an operator. Fig. 1 depicts the network architecture and the entire procedure used to execute our method. The detailed procedures are the following.

### *A. Extract of intracranial region*

We remove the skull and dura mater regions from original images for extracting cerebral parenchyma (GM and WM) and CSF regions. For removing these regions, first we convert to a binary image that consists of the background, skull, dura mater, and intracranial regions using Otsu's method [8]. Subsequently, we extract the largest object in the binary image. After filling the inside of the object, an intracranial region is extracted without skull regions. Nevertheless, dura mater sometimes remains in the intracranial regions, depending on the target image. Dura mater is distributed between the skull and intracranial regions. In this report, we introduce Level Set Methods (LSMs) to extract intracranial regions without dura mater after extracting the object using Otsu's method. Actually, LSMs have been attractive for use as a topology-free deformable model that enables separation or combination of contours. The contour frames (shrinkage, expansion, curvature, transformation, etc.) are expressed by Partial Differential Equation (PDE) [9]. The PDE updates the progress of the contour. The LSMs are effective to extract intracranial regions' contours of different sizes and shapes with transformation, separation, and combination of the contours. For the initial contour of LSMs, we use the contour around the object extracted using Otsu's method. The contour based on PDE depends on a brightness gradient or the energy of an image. For that reason, we use LSMs that can extract intracranial regions irrespective of dura mater with low brightness.

### *B. Nonlinear quantization with SOMs*

Fig. 2(a) depicts a brightness histogram of a head MR image. The boundaries of brain tissues are not clear in the histogram because of the nonlinear brightness characteristic and wide dynamic range. Therefore, we use the self-mapping capability of SOMs to create categories to quantize the brightness distribution from topological relations of features in head MR images. We can classify input features while maintaining topological relations through learning based on neighborhood regions. The number of created categories depends on the number of mapping layer units. In this study, our segmentation targets are three tissues: CSF, GM, and WM. The segmentation results are not correspondent to these tissues if the number of mapping layer units is less than five units. The narrow mapping space of the insufficient number of units cannot express the brightness distribution of images. Therefore, we increased mapping layer units for improving the classification performance of SOMs. Fig. 2(b) depicts a result of nonlinear quantization of the brightness histogram with SOMs. The brightness histogram is quantized according to the brightness characteristics and tissue boundaries. While spreading the mapping space, granular segmentation is possible for the brightness distribution of a wide dynamic

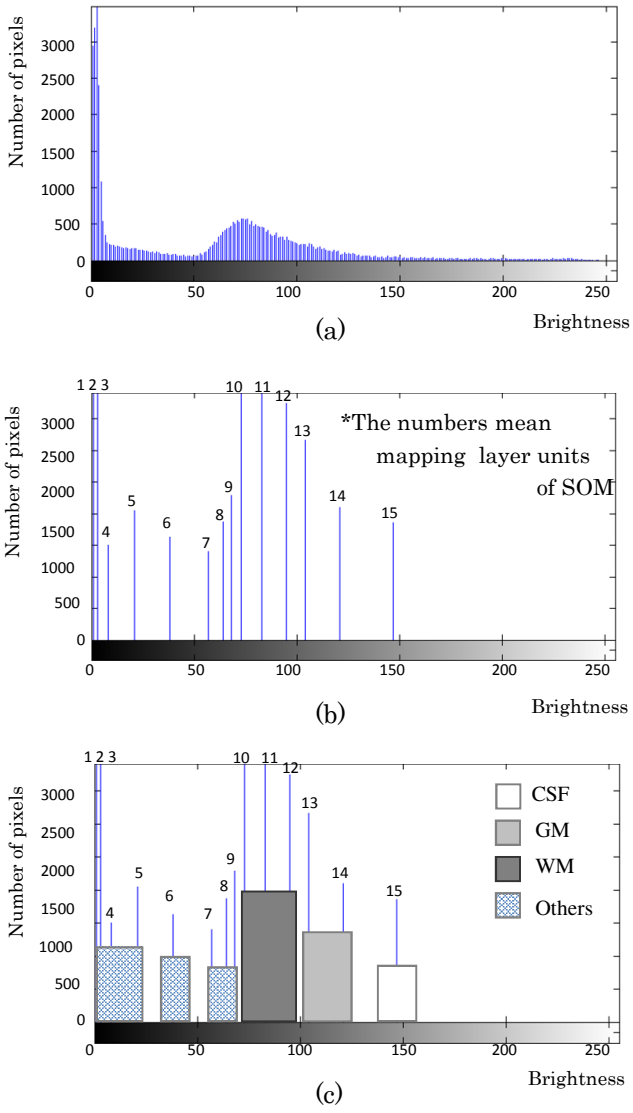


Fig. 2. Brightness histogram of a head MR image: (a) histogram of brightness by original image, (b) histogram of segmented categories with nonlinear quantization of SOMs, (c) histogram of integrated categories with Fuzzy ART.

range. We evaluate the number of mapping layer units in detail through a preliminary experiment described in the next section.

The input features for SOMs are a brightness value of an attention pixel and various features from a local block. The local block is chosen from a selected pixel that is extracted randomly from the target image. Subsequently, we calculate features of the brightness distribution, edge, and texture information in the local block. The input features of SOMs are a brightness value, an average brightness value, a difference value for the maximum brightness, and a difference value for the minimum brightness from the local block. When we use only brightness values, the WM regions and GM regions are mixed. The result indicates that head MR images appear to have similar brightness values in the different tissues. Moreover, in this case, the segmentation result includes many noise pixels because the input feature is treated as independent information in each pixel and the brain tissue continuity is not considered. Therefore, we use the average brightness value as the feature of the continuity of tissues and the difference values for the maximum and minimum brightness as the boundary between tissues [10].

The SOMs are unsupervised neural networks of competitive learning for self-mapping in a low dimension space that maintain the topological relations of multidimensional input data [11]. In fact, the SOMs save topological relations of characteristics and have a characteristic of self-mapping inside of the network. Therefore, similar tissues are obtainable using topological characteristics of SOMs. The training algorithm of SOMs is the following.

1) Let $w_{ij}(t)$ be the weight from the input unit $i$ to the Kohonen unit $(n, m)$ at time $t$. The weights are initialized with random numbers.
2) Let $x_i(t)$ be the input data to the input unit $i$ at time $t$. The Euclidean distance $d_j$ between $x_i(t)$ and $w_{ij}(t)$ is calculated as

$$d_j = \sqrt{\sum_{i=1}^{n}(x_i(t) - w_{ij}(t))^2}. \quad (1)$$

3) The win unit $c$ for which $d_j$ becomes a minimum is defined as

$$c = argmin(d_j). \quad (2)$$

4) Let $N_c(t)$ be the units of the neighborhood of the unit $c$. The weight $w_{ij}(t)$ inside $N_c(t)$ is updated using the Kohonen training algorithm as ($\alpha(t)$ is training coefficient, which decreases with time.)

$$w_{ij}(t+1) = w_{ij} + \alpha(t)(x_i(t) - w_{ij}(t)). \quad (3)$$

5) Training is finished when the iterations reach the maximum number.

In our method, the initial value of $\alpha(t)$ is set as 0.5, and the initial of $N_c(t)$ is set as 2/3 of the number of mapping layer units. It is designed so that both values decrease linearly with time. The number of learning operations is set empirically as 20,000.

### C. Integrating categories with Fuzzy ART

Fuzzy ART is a theoretical model of incremental learning neural networks that enables the retention of stability and plasticity together [12]. We use weights of SOMs for training data of Fuzzy ART. The brightness histogram of head MR images is quantized nonlinearly using SOMs. Fig. 2(c) depicts the integration results of categories with Fuzzy ART. The brightness distribution that is quantized nonlinearly by SOMs does not accommodate brain tissues, depending on the number of mapping layer units of SOMs. Using Fuzzy ART, classification results that correspond to brain tissues are obtained according to the order of brightness while maintaining a relation between categories classified by

SOMs. Irrespective of the target image, the number of target brain tissues is fixed. Therefore, in T2-weighted images, the order of the brightness distribution is: CSF is the highest; GM and WM are the second and third, respectively; and the background is the lowest. Therefore, the mapping colors are assigned in the above order in accordance with the magnitude of weight vectors.

Fuzzy ART makes it possible to integrate the category in a constant scale of the vigilance parameter that controls the classification granularity. We decide the vigilance parameter in the preliminary experiment at the next section. The Fuzzy ART algorithm is the following: $I$ is an input $m$-dimensional vector. The quantities of neurons of the F1 and F2 are, respectively, $M$ and $N$. Fuzzy ART dynamics are determined using the choice parameter $a(a > 0)$, the learning rate parameter $r(0 \leq r \leq 1)$, and the vigilance parameter $\rho(0 \leq p \leq 1)$.

1) $w_i$ are the weights between each F2 neuron $i$ and each corresponding F1 neuron. All $w_i$ are initialized as one.
2) For each input $I$ and each neuron $i$, the choice function $T_i$ is defined as

$$T_i = \frac{|I \wedge w_i|}{a + |w_i|}, \tag{4}$$

where the fuzzy AND operator are defined as

$$(n \wedge v)_j \equiv min(u_j \wedge v_j), \tag{5}$$

and where the norm is defined as

$$|u| \equiv \sum_{j=1}^{m} |u_j|. \tag{6}$$

3) $i_0$, which is the maximum value of $T_i$, is selected for a category as a winner. The category with the smallest index is chosen if more than $T_i$ is maximal. When $i_0$ is selected for a category, the $i_0$ the neuron on the F2 is set to 1 and other neurons are set to zero.
4) Resonance or resetting is judged as 5) if the selected category at 2) and 3) matches the input data $I$.
5) Resonance occurs if the match function of the chosen category meets the vigilance criterion. The weight vector $w_{i0}$ is updated as

$$w_{i0} = r(I \wedge w_{i0}) + (1 - r)w_{i0}. \tag{7}$$

6) If $I$ has no resonance to $i_0$, then $i_0$ is reset. The network seeks the next category $T_i$ to be maximal and reselects it. The network determines resonance or it resets. If all categories are reset, then go to 7).
7) A neuron is created on F2 and a new category is registered. Steps 2)–7) are controlled by $M$ and $K$ and are repeated $M \times K$ times to be presented sequentially of $I$.

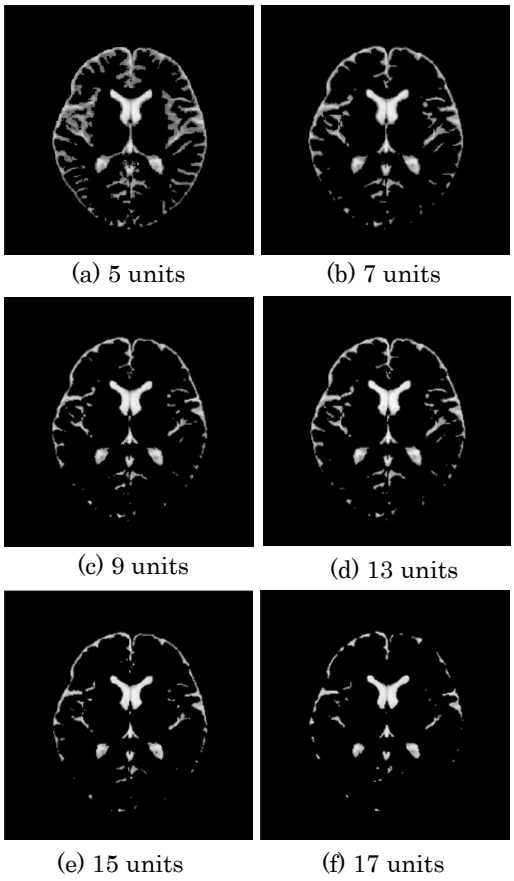


Fig. 3. Segmentation results of CSF according to the number of mapping layer units: (a)–(f) from 5 units to 17 units step by 2 units, expect of 11 units.

## III. Preliminary experiment

In this section, we present an evaluation of the number of mapping layer units of SOMs and the vigilance parameter of Fuzzy ART. We use five samples of head MR images for research use in each generation from 30s to 70s. The resolution of head MR images is 512 $\times$ 512 pixels. We convert the brightness level from 16 bit to 8 bit using linear quantization.

### *A. Mapping layer units (nonlinear quantization)*

The structure of brain tissues differs from mapping layer units of SOMs corresponding to the target images. Especially in T2-weighted images, the segmentation of cerebral parenchyma to WM and GM is a challenging task because the brightness gap separating them is slight. We set a high granularity mapping space to segment in each target image. We evaluate the number of mapping layer units to change from 5 units to 17 units. For creating the same number of units around the burst unit, we increased the total number of unit steps by two units. Fig. 3 shows the segmentation results of CSF regions. For five units, the CSF regions that show high brightness are expanded to GM regions. In this case, CSF regions and high-brightness GM regions are mapped to one unit because the mapping space is insufficient for

segmentation. From seven units, the segmentation results are improved according to the increment of the number of mapping layer units. In the case of 17 units, a non-burst unit that is assigned no pixels of head MR images is apparent. In our method, we set the mapping layer to 15 units, which is a sufficient mapping space, and all units are burst.

### *B. Vigilance parameter (integration granularity)*

The Fuzzy ART responds sensitively to changed parameters. The classification granularity is controlled mainly by the vigilance parameter $\rho$. For evaluation of this parameter, we set $\rho$ as 0.800–0.950, with steps by 0.025. Fig. 4 shows three samples of segmentation results ($\rho$=0.850, 0.875, and 0.900). We specifically examine GM and WM regions segmentation results because CSF regions are not changed with $\rho$. For $\rho$ higher than 0.900, the GM regions are divided into several categories with finer classification granularity. For $\rho$ of 0.900, GM regions are divided into two categories. The boundaries of tissues remain as independent tissues that are not integrated according to brain tissues. For $\rho$ lower than 0.850, GM and WM regions are segmented extensively. For $\rho$ of 0.850, the segmentation result GM appears as a consecutive cingular of the region along the boundary of the CSF and the WM. However, for some images, GM regions and WM regions are integrated into one category. For $\rho$ of 0.875, GM regions appear at the cingular of the region at the boundary between CSF and WM against any images. Based on observation by a diagnostician, this result is matched to the anatomical brain structures. Therefore, we set the vigilance parameter to 0.875.

## IV. Evaluation experiment

We use clinical head MR images of 30 men and women in their 30s–70s in this section. The head MR images were taken at brain dock examinations. The resolution of head MR images is 512 $\times$ 512 pixels. We convert the brightness level from 16 bit to 8 bit using linear quantization.

### *A. Extraction results of intracranial region*

We applied LSMs to failed images obtained using Otsu's method in which the dura mater and the intracranial region are in contact. Fig. 5 shows an extraction result near the frontal lobe in intracranial regions using LSMs. The dotted line shows the LSM contour upon which is constructed the surface of the intracranial region. The brightness gradient of intracranial regions is higher than that of the dura mater. Therefore, LSMs can remove dura mater that cannot be removed using Otsu's method.

### *B. Segmentation results*

Fig. 6 shows comparison results of segmentation tissues obtained using our method and the former method [7]. In the former method, the CSF and GM regions are segmented extensively. In the former method, the mapping layer is fixed to five units. We consider that the number of the mapping layer units is inadequate for mapping the brightness characteristics of the head MR image. Moreover, the brightness characteristics corresponding to the tissues differ in each target image.

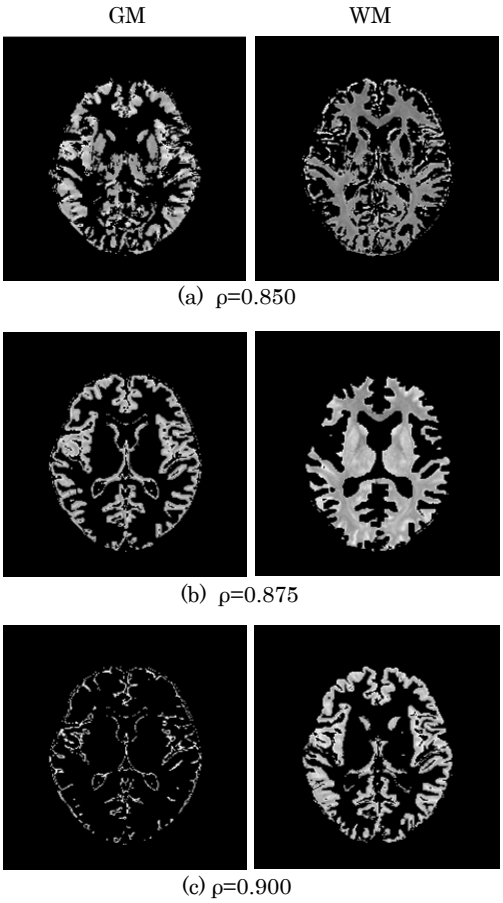


Fig. 4. Segmentation results of GM and WM according to vigilance parameters: (a)–(c) of 0.850–0.900, with steps of 0.025.

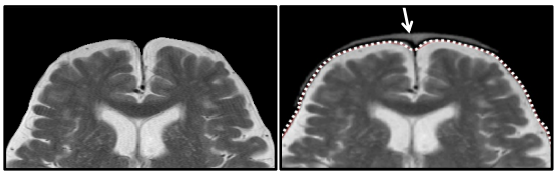


Fig. 5. Extraction result near the frontal lobe in an intracranial region using LSMs: (a) ground truth created by a diagnostician, (b) the dotted line shows the contour extracted by LSMs, the arrow shows the dura mater.

In contrast, our method can segment the CSF regions along with high-brightness regions, although the boundary between CSF and GM regions show a similar contrast. The GM shows consecutive band-shaped regions to the boundary between CSF and WM regions. Therefore, segmentation results that reflect the continuity and marginal information of the brain tissues are obtained.

### *C. Application to clinical head MR images*

Fig. 7 shows segmentation results of the CSF, to which we devoted attention for quantification of brain atrophy. From

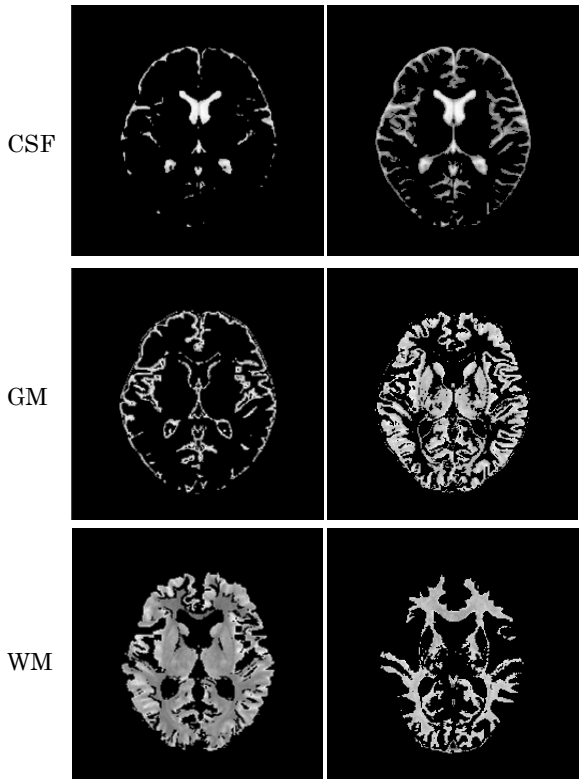


Fig. 6. Comparison results of segmentation tissues: (a) our method, (b) the former method.

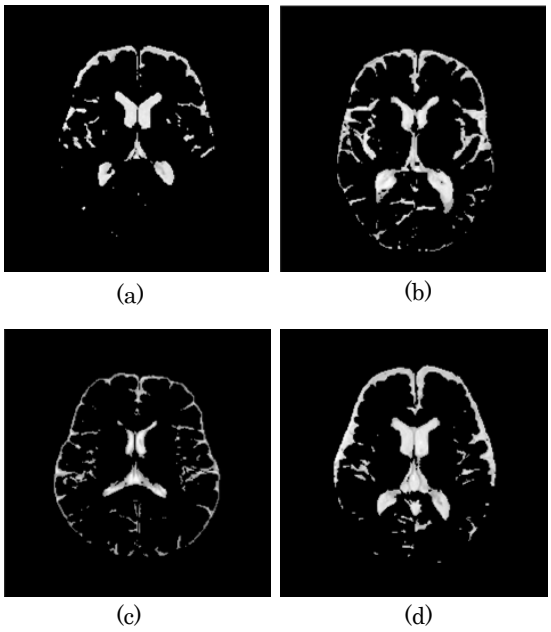


Fig. 7. Segmentation results of CSF for clinical head MR images taken at brain dock examinations: (a) 60s, male; (b) 70s, male; (c) 40s, female; (d) 70s, female.

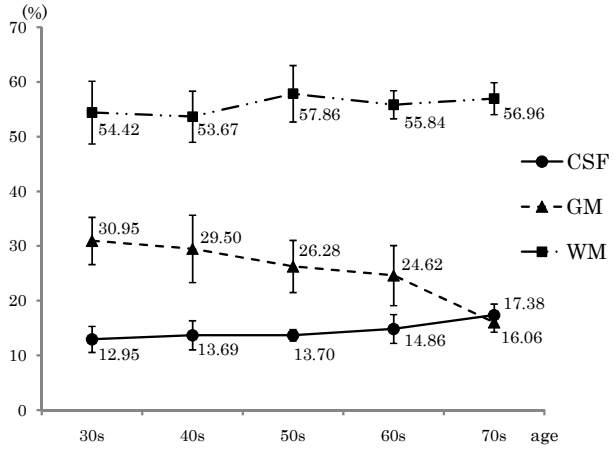


Fig. 8. Volume rates of segmented tissues (CSF, GM, and WM) by age.

the clinical head MR images, we selected four typical images that show a distinction of the brightness distribution. The CSF regions are segmented definitely along high-brightness pixels and the boundaries between CSF and GM, although these images contain individual variations of brain structure characteristics. The high-brightness regions are segmented with high granularity of the mapping space to be assigned 15 units of the mapping layer of SOMs. We obtained the results reflected by the assignment of GM and WM regions of low brightness for integration by Fuzzy ART. In the judgment of a diagnostician, the segmentation results are evaluated as matched to the brain structures.

According to the volume rates of respective target tissues, we measured structural changes of the brain that occur with aging. We applied our method to an MR image database comprising clinical head MR images. Our method can produce a suitable assignment of the mapping space for a target image with various brightness distributions. Fig. 8 depicts volume rates of segmented tissues (CSF, GM, and WM) by age. In the intracranial region, CSF regions are increased and GM regions are decreased by aging. From this result, we observe a significant correlation between aging and expansion of CSF.

## V. Conclusion

This paper presented an unsupervised segmentation method that hybridized SOMs and Fuzzy ART based solely on the brightness distribution and characteristics of head MR images. For the intracranial region extracted by LSMs, we segmented it with high granularity using SOMs and integration of three regions (CSF, GM, and WM) using Fuzzy ART while maintaining relations of anatomical structures of brain tissues and the order of brightness on T2-weighted MR images. We obtained the following results.

- Using LSMs as a deformable model, our method can extract intracranial regions without the dura mater that remains when using Otsu's method.
- With expansion of the mapping layer from 5 units to 15 units, our method can segment CSF regions along with high-brightness regions according to brain structures.
- For application to clinical head MR images, segmentation results are matched to the anatomical brain structure evaluated by a diagnostician.

- For application to an MR image database comprising clinical head MR images, significant correlation between aging and expanding of CSF was found.

We produced a process that is useful to provide objective information for use in support of brain atrophy diagnosis. Future studies will be undertaken to optimize LSM parameters using evolutionary learning based methods, e.g. Genetic Algorithms (GAs). Moreover, we will apply Active Appearance Models (AAM) for extraction of sagittal sinus regions.

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