Segmentation of MR Brain Images : A Fuzzy Logic Approach

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Abstract

An approach is developed to MR brain images segmentation, based on pixel classification using Fuzzy Rule Based system and Fuzzy Similarity measures. The cerebral images are segmented into gray matter, white matter, and cerebrospinal fluid (CSF). Image preprocessing was first done to improve the quality of brain MR images and reducing artifacts. The feature vector was selected to be the pixel and its eight neighbours. The two methods implemented are of supervised nature where in the first we build fuzzy rules while in the second we build fuzzy prototypes. The classification in the first method uses fuzzy inference and implication techniques to derive the classes of images. The classification in the second method uses pattern matching and fuzzy similarity measures. These methods are tested using sets of MRI brain images. The results show the efficient and robust performance of these algorithms. In this paper a comparison of these algorithms with Fuzzy C-Means algorithm is presented.

Keyword-I: Medical Imaging

Keyword-II: Biomedical Application, Cerebrospinal Fluid, Feature Identification and Classification, Fuzzy C-Means, Fuzzy Logic, Fuzzy Rule-Based System, Fuzzy Set Theory, Fuzzy Similarity Measures, Gray Matter, Image Segmentation, Image Processing, Magnetic Resonance Imaging, Pattern Recognition, Rule Extraction, Rule Formulation, Supervised Learning, White Matter.

1. Introduction

Quantitative analysis of brain tissues (white matter, gray matter, cerebrospinal fluid (CSF)) is important for clinical investigations [1]. Determination of different brain tissue volumes is valuable for progress of therapy process and planning, surgical planning and 3-D visualization of brain matter for diagnosis and abnormality detection [2].

MR brain images are analyzed by qualitative or semi-quantitative visualization and evaluation.

Brain tissues can be categorized as white matter, gray matter, cerebrospinal fluid (CSF) or vasculature. Segmentation for these types of tissues is important for volumetric calculations, cortex flattening, and 3D reconstruction of brain tissues.

A review of MRI segmentation methods and applications and the theoretical basis of these methods have recently been presented in literature [3,4].

Fuzzy Logic provides an algorithm which can convert linguistic rules into a decision strategy [5]. The set of linguistic description rules is based on expert knowledge. From these set of rules, the inference mechanism will provide a linguistic decision [6]. Fuzzy techniques in pattern recognition were presented in the area of control and medical diagnosis of diseases [7,8]. Fuzzy similarity measures and its application in object matching is an active area of research in the field of medical diagnosis [9].

2. Materials and Methods

2.1 MR Brain Image Pre-processing

MR images contain noise in the background. This noise can affect the segmentation quality of the image. So thresholding algorithm [10] is used over the image to identify the background and then label it by a constant graylevel (0). Since the skull, scalp, and fat in the original brain image do not contribute to brain tissue and are not clinically significant, we process the images to exclude these unwanted structures before the segmentation phase [11] in order to achieve better segmentation of brain tissues.

2.2 Algorithm I -Fuzzy Rule Based System

After the MRI slice image of 256*256 size is preprocessed and the skull is removed the user selects at least 10 points in every region of white matter, gray matter, and CSF. The features used in the two segmentation algorithms are the selected pixel intensity and its eight neighbours pixel intensities. Then the feature vector is of dimension 9 of graylevels. These vectors for each class are first fuzzified using the defined membership functions of 5 fuzzy sets each as shown in Figure 1. The set of vectors for three classes of tissues were used to derive the fuzzy rules. The selected vectors are tested to generate different fuzzy rules. Fuzzy logic provides an algorithm which can convert linguistic rules into a decision strategy [5]. The set of linguistic description rules is based on expert knowledge. From this set of rules, the inference mechanism will provide a linguistic decision.

The generalized modus ponens (GMP) plays an important role in this process. The simplest form of **GMP** is : fact 1: x is A' , fact 2: IF x is A THEN y is B , consequence: y is B' where A,B,A',B' are fuzzy sets and x, y are linguistic variables. Several methods of inference mechanisms are based on this form of approximate reasoning. The most important inference mechanism is the compositional rule of inference suggested by Zadeh [5]. The general form of this compositional operator is denoted by sub star composition [12]. $y = x \circ R$, where $\circ$ represents the compositional operator and R is a fuzzy relation represented by any fuzzy implication function. The fuzzy rule in the form of "**IF** x is A and y is B **THEN** z is C", is a fuzzy relation R defined as follow:

$$\mu_R \triangleq \mu_{(A \text{ and } B \to C)}(u,v,w) = [\mu_A(u) \text{ and } \mu_B(v)] \to \mu_C(w)$$

Where "A and B", are fuzzy sets $A \times B$ in $U \times V$ and $R \triangleq (A \text{ and } B) \to C$

is a fuzzy implication in $U \times V \times W$.

Nearly fourty distinct fuzzy implication functions have been described in the literature [10]. The most well-known implication function is described by Mamdani and Larsen and listed in [12].

In recent years many techniques of medical diagnosis have attempted to model the relation between the diseases and symptoms using fuzzy logic [8,13,14]. In our approach the medical knowledge is represented by a fuzzy relation R between the MRI graylevels features and class (WM, GM, CSF). Thus, given the fuzzy set S of the measured features calculated from the MRI image, the fuzzy set D of possible anatomy can be inferred by the compositional rule of inference, $D = S \circ R$.

We extracted the fuzzy relation R from numerical data using the method suggested by Wang and Mendel [6].

2.2.1 Rules extraction steps:

step 1. Assume the domain intervals for each parameter ,where the domain interval of a variable means that most probably this variable will lie in this interval (256 graylevels). Divide each domain interval into 5 regions denoted by *Very Low, Low, Medium, High,* and *Very High*. Assign each region a certain fuzzy membership function. We have chosen three forms of membership functions, the triangle form, the trapezoidal form and the bell form. By adjusting the ranges of the membership functions, it was found that the bell shape is the best shape to be selected. The equation of the bell form used in the analysis is given as follow:

$$\boldsymbol{m}_s(s) = e^{-[(s-\overline{s_m})^2/2s^2]}$$

where μ_s denotes the membership function of a fuzzy value as shown in Figure 1. Choosing the fuzzy singleton ($\overline{s}_m$) for each fuzzy set depends on two criteria: 1-statistical basis 2- expert knowledge.

The crossover point was set to be at 0.5 as shown in Figure 1. In this sense a dominant rule always exists and is associated with the degree of belief greater than 0.5. The output which is a linguistic variable called the segmented region, has three fuzzy values named White Matter, Gray Matter and Cerebrospinal Fluid .

step 2. First, determine the membership degrees for each of the given parameters $G1_i$, $G2_i$, $G3_i$, $G4_i$, $G5_i$, $G6_i$, $G7_i$, $G8_i$, and $G9_i$ in all the different regions .

step3. Rules validation, as every pixel generates one rule, it is probable that there will be some conflicting rules, i.e., rules that have the same **IF** part but have different **THEN** part. In our case no conflicted rules were reported. When the case of two rules having the same if and then part then the highest strength one replaces the lowest strength one.

2.2.2 Inference Mechanism

The inference mechanism used was based on *SUP MIN* compositional rule of inference

The connective *and* is commonly used as the *min* operator, while the connective *or* defined as the *union* operator. The firing strength for each rule is as follows :

$$\boldsymbol{a}_{R_i} = \boldsymbol{m}_{G1_{R_i}}(G2) \wedge \boldsymbol{m}_{G2_{R_i}}(G2) \wedge \boldsymbol{m}_{G3_{R_i}}(G3) \wedge \boldsymbol{m}_{G4_{R_i}}(G4) \wedge \boldsymbol{m}_{G5_{R_i}}(G5)$$
$$\wedge \boldsymbol{m}_{G6_{R_i}}(G6) \wedge \boldsymbol{m}_{G7_{R_i}}(G7) \wedge \boldsymbol{m}_{G8_{R_i}}(G8) \wedge \boldsymbol{m}_{G9_{R_i}}(G9)$$

where i runs along all the pixels, $\wedge$ is the minimum operator. For each class of the three anatomical regions, we use the *max* operator for the firing strength corresponding to this class.

$$\boldsymbol{a}_p = \max(\boldsymbol{a}_{White Matter}, \boldsymbol{a}_{Gray Matter}, \boldsymbol{a}_{Cerebrospinal Fluid})$$

where p denotes the anatomical region and the decision is made based on α_p . Finally we select among the three classes of regions the one with the highest value and consider the new pixel to belong to the corresponding class. The confidence of an unknown pixel (the rest of all image pixels) characterized by its crisp data (9 graylevels) will be low ($\alpha_p < 0.5$) if its data is

far from that data used to generate the rules. As long as the data of an unknown pixel is close to the data used for generation of any of the rules, the firing strength of the corresponding class of tissue, α_p will be greater than 0.5.

If there are two equal firing strength then the decision will be made for probability of both classes then we assign the pixel to the one having the highest strength of the two pixels located on the primary 1st order neighbourhood.

2.3 Algorithm II -Fuzzy Similarity Measures System

2.3.1 Measures of Equality Between Two Fuzzy Quantities

In this section, we will summarize some existing approaches that are useful for determination of a degree of equality (degree of matching) for two fuzzy quantities. Let us focus our attention on the comparison of two fuzzy sets A and B defined in the same universe of discourse X, say A, B: X [0,1].

2.3.1.1 Distance Measure

A board class of measures of equality is based on distance measure. Usually, a general form of Minkowski r-metric is given as:

$$d_n(A, B) = \left(\int_{-\infty}^{\infty} |A(x) - B(x)|^r \, dx \right)^{1/r} \quad r \geq 1 \tag{1}$$

2.3.3 Set-Theoretic considerations

The second class of measures of equality originates from some basic set-theoretic considerations.

• Based upon the dissimilarity measure defined as the ratio:

Card $(A \cap B)$ / Card $(A \cup B)$ (2)

• Possibility measure of two fuzzy sets. The measure describes the highest degree to which these two fuzzy quantities A and B overlap,

$$\pi(A, B) = \sup_{\chi \in X} [\min (A(x), B(x))] \tag{3}$$

2.3.1.3 Logical framework

The third way of dealing with the comparison of two fuzzy quantities is performed in a logical framework. One among well-known approaches in this group refers to linguistic evaluation of two fuzzy quantities that leads directly to notions of fuzzy logic (a so-called fuzzy truth values). For a certain element of the universe of discourse X, a degree of equality [9,15] of a and b, a, b, $\in [0,1]$ is equal to: $a \equiv b = \left\{ (a \rightarrow b) \wedge (b \rightarrow a) + (\overline{a} \rightarrow \overline{b}) \wedge (\overline{b} \rightarrow \overline{a}) \right\}$ (4)

Here $\wedge$ stands for minimum, $\rightarrow$ forms an implication and $\overline{a}$ =1-a. Then applying conjunctions known in fuzzy sets, the aforementioned formula is translated into the form plausible for computational purposes. Simply speaking the implication $\rightarrow$ is modelled by various pseudo complements induced by corresponding t-norms e.g., for the t-norm [16] specialized as minimum reads as :

$$a \equiv b = \begin{cases} (1 + b - a) & \text{if } a > b \\ 1 & \text{if } a = b \\ (1 + a - b) & \text{if } a < b \end{cases} \tag{5}$$

The last method of matching of two fuzzy quantities is closely related to an essence of computations with fuzzy sets. Therefore, in further discussion we will concentrate on the studies on the equality index as given by method 3. Additionally this third approach enables us to perform a point wise matching process. In the case of the third type of these measures it is sometimes of interest to have a mechanism within which one combines the grades of equality to get a single number specifying an overall characterization of equality of the fuzzy set. At least three basic methods for aggregation are often utilized and we will add to this list the fuzzy integrals method and we will discuss it later [9,13,14].

2.3.2 Fuzzy measure

When we consider a certain set X, the function g that makes subset E and F correspond to the values in the interval [0,1] are called fuzzy measures [15].

2.3.3 Fuzzy integrals

The fuzzy integral [9,15,16] of function h: X - [0,1] on E $\subset$ X by fuzzy measure g is defined as follows:

$$h(x) \circ g = \max_{E \subset X} \left[\min_{x \in E} (h(x)) \wedge g(E) \right]. \tag{6}$$

2.3.4 Proposed Method For Pattern Matching

Many techniques for pattern matching and classification using fuzzy logic have been proposed, and now used in many applications such as speech and character recognition, medical diagnosis [17-19] and decision making. In the following

paragraph we will introduce a proposed method for image segmentation based on the fuzzy similarity measures of the unknown pixel and the sets of prototypes from a known selected pixels associated with anatomical regions.

Give a vector $X = \begin{bmatrix} x_1\, x_2 & \ldots\ldots\ldots x_{n-1} & x_n \end{bmatrix}^T$, where n is the dimension of the vector X and the number of the classification parameters (features) in the system (see Figure 2).

x_i denotes the measured ith feature of the event, and X represented as a point in nth dimensional vector space $U_x$consisting of m ill defined pattern classes $C_1, C_2,..,C_j,..C_m$,let R_1, $R_2...R_j,...,R_m$ be the reference vectors where R_j associated with C_j containing h_j number of prototypes such that:

$$R_j^{(1)} \in R_j \qquad 1 = 1,2,...h_j \tag{7}$$

The pattern X can then be assigned to be a member of that class if it shows maximum similarity to this class (see Figure 2).

2.3.5 Fuzzification process.

The fuzzification is done by getting the value of the membership functions to obtain a fuzzification matrix $\aleph$ of dimension z*n where z is the number of the linguistic values for the linguistic variables and $x_{ij} = F_{ij}(x_i)$

where F_{ij} is the membership function of the linguistic value i for the fuzzy value j.

We do the fuzzification for the X and all Rj's.

2.3.6 Similarity Measures

So the problem now is how to measure the similarity between $\aleph$ and R_j^l and obtain the over all similarity of this X and the other classes C_j represented by the R_j prototypes. As described in the previous sections that many techniques can be used as: distance measure, from fuzzy set theories, and linguistic evaluations. If the implication is chosen *min*(see equations 4-5),

so given $\aleph$ and Fuzz $(R_j^1) = R_j^l$ by using the linguistic evaluation we obtain the similarity matrix S_j^l.

$$\aleph = \begin{bmatrix} x_{11} & \cdots & x_{1j} & \cdots & x_{1n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ & & x_{ij} & & \\ & & \vdots & & \\ x_{z1} & & & & x_{zn} \end{bmatrix}, R_j^l = \begin{bmatrix} r_{11} & \cdots & r_{1j} & \cdots & r_{1n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ & & r_{ij} & & \\ & & \vdots & & \\ r_{z1} & & & & r_{zn} \end{bmatrix}, S_j^l = \begin{bmatrix} s_{11} & \cdots & s_{1j} & \cdots & s_{1n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ & & s_{ij} & & \\ & & \vdots & & \\ s_{z1} & & & & s_{zn} \end{bmatrix} \tag{8}$$

where $\qquad S_{ij} = x_{ij} \equiv r_{ij}$.

Two methods can be used to get the similarity index between the $\aleph$ and R_j^l.

The first is to obtain the similarity vector H as follow:

$$H_j^l = \left[\frac{1}{z}\sum_z f(s_{z1}) \cdots \frac{1}{z}\sum_z f(s_{zn}) \right] = \begin{bmatrix} h_1 \ldots h_n \end{bmatrix} \tag{9}$$

where f is a suggested function for re-weighting the linguistic evaluation. Many functions can be used to do this re-weighting, such as sigmoid, hard, s functions[9]. Then we obtain the similarity index S_j^1

$$S_{H_j}^1 = \frac{1}{n}\sum_n h_n \tag{10}$$

which represents how similar is this unknown pixel to the category j, prototype *l*.

The second method to get the similarity index between $\aleph$ and R_j^l is by using the fuzzy integral as given in equation (6), where h *re*presents the similarity function and *g* represents a simple fuzzy measure which is the cardinality of the set E , then $E \in X$ and X is the power set of the X.

If we apply the fuzzy measure described before to the S_j^l rows then we get:

$$S_j^l = \begin{bmatrix} R_1 \\ \vdots \\ R_z \end{bmatrix} \text{ where } R_i = \begin{bmatrix} s_{1i} & \ldots & s_{ni} \end{bmatrix}, \qquad HG_j^l = \begin{bmatrix} hg_1 \\ \vdots \\ hg_z \end{bmatrix} \tag{11}$$

where hg_i is the fuzzy integral of the row i in the S_j^l matrix.

2.3.7 Aggregation methods

Many criteria can be selected to get the similarity between X and the category j, such as follows:

$$a) \ S_j = \max_l \ S_j^1 \qquad b) \ S_j = \min_l \ S_j^1 \qquad c) \ S_j = \frac{1}{l}\sum_l S_j^l \qquad (12)$$

Note that S_j^1 can be $S_{G_J}^l$ or $S_{H_J}^l$

3. Results and Discussion

The proposed segmentation algorithms are applied to two types of data sets. The first is acquired from a GE 1.5 Tesla of a T1 MR images of brain axial slices of thickness 1 mm with a slice resolution of 256*256 and the second is simulated images of the same specs downloaded from [20]. Each data set consists of 60 slices. Figure 3 shows an example of the output of the preprocessing step for a slice from the real data set (Figure 3-a). Figure 3.b illustrates only the brain tissues after the removal of unwanted structures (skull,scalp, and fat). Figure 4 shows the results of segmentation using Fuzzy Rule-Based algorithm. Figure 4.a shows a slice of simulated image. Figure 4.b and 4.c show the segmented results using Fuzzy Rule-Based algorithm of Figures 4.a and 3.b, respectively. Figure 5 shows the result of segmentation using the Fuzzy Similarity measures algorithm. Figure 5.a shows a slice of a simulated images, and Figure 5.c shows a real slice. Figures 5.b and 5.d show the segmented results using Fuzzy Similarity measures of Figures 5.a and 5.c. We have compared the segmentation results for the two proposed algorithms with manual segmentations of the three tissue types and constructed a confusion matrices to calculate the extent of misclassification. Tables I and II show the confusion matrices for the results of segmentation using Fuzzy Rule-Based algorithm for the simulated MR images and the real images, respectively. Table III and IV show the confusion matrices for the results of segmentation using Fuzzy Similarity measures algorithm for the simulated MR images and the real images, respectively. The rows in the confusion matrix indicate each tissue which have been segmented manually. The columns indicate the percentage of that tissue classified by the segmentation algorithm. For example in Table 1 for the manually classified white matter of the simulated images, Fuzzy Rule Based algorithm classified 1.6 % as gray matter, 98 % as white matter, and 0.4 % as CSF. From Figures 4,5 and Tables I-IV illustrating the results of the two proposed fuzzy segmentation algorithms, the segmented simulated images are apparently more accurate than the real segmented images. This can be contributed to the image noise caused by the acquisition process of the real images. Our segmentation algorithms can be improved by using, beside the pixel and neighbourhood, other features like texture features [21]. The results of segmentation using the Fuzzy Rule-Based system for the three anatomical structures (White matter, Gray matter, CSF) are comparable and promising. The fuzzy similarity measures algorithm results indicate that the CSF segmentation accuracy is better than that of gray matter than that of white matter. In comparison to our proposed algorithms of segmentation, Fuzzy C-Means [4] results are shown in Figure 6 and Table V which show slightly better accuracy of segmentation with respect to fuzzy similarity measures algorithm, but comparable to fuzzy rule based algorithm for all the three anatomical structures for most of the slices used in segmentation. One of the most important advantages of the fuzzy rule based algorithm is its very low computation time and the learning phase of the systems is just extracting rules after fuzzification and most operations are Min and Max operations. The min and max operation are used in fuzzification, rule evaluation, and defuzzification in the first system (Fuzzy Rule-Based), and fuzzy matrices matching in the second system (Fuzzy Similarity measures). The computation times (using PC PII 333MHz 128Mbyte RAM) for the two proposed algorithms as well as for the FCM are shown in Table VI. It is obvious that the Fuzzy Rule-Based algorithm is the fastest one followed by the Fuzzy C-Means and the slowest one is the fuzzy similarity measures which require matrices matching for every pixel, i.e. matching every pixel with all prototypes.

4. Conclusion

We have proposed two new algorithms for segmentation of MR brain images which provide an acceptable segmentation of the three brain anatomical structures based on fuzzy logic. The two proposed algorithms are of supervised nature where minimal manual intervention is done by the expert user (Radiologist) to select pixels (10-15 pixels are sufficient) from each the three anatomical brain structures (White matter, Gray matter, and CSF) and uses these small number of the expert selected pixels associated with these anatomical brain structures to simply derive the fuzzy rule based system or building the fuzzy prototypes. The fuzzy rule based system is very fast on the PC and this advantage could be used in the 3D brain MRI reconstruction and visualization applications. Our future work is to improve our segmentation results by utilizing texture feature parameters (in addition to the used features).

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Table I: Confusion matrix for the results of segmentation of the simulated MR brain images(15 slices) using Fuzzy Rule-Based algorithm. Each row shows the % of each tissue which has been classified as every other tissue .

Tissue	Percent of Manual Segmentation classified by Fuzzy Rule-Based Algorithm For the Simulated images		
	Gray	White	CSF
Gray	97	2.1	0.9
White	1.6	98	0.4
CSF	3.1	0.9	96

Table II: Confusion matrix for the results of segmentation of the real MR brain images(15 slices) using Fuzzy Rule-Based algorithm. Each row shows the % of each tissue which has been classified as every other tissue .

Tissue	Percent of Manual Segmentation classified by Fuzzy Rule Based Algorithm For the Real images		
	Gray	White	CSF
Gray	93	4.1	2.9
White	2.8	96.5	0.7
CSF	1.2	0.8	98

Table III: Confusion matrix for the results of segmentation of the simulated MR brain images(15 slices) using fuzzy similarity measures algorithm. Each row shows the % of each tissue which has been classified as every other tissue .

Tissue	Percent of Manual Segmentation classified by Fuzzy Similarity Measure Algorithm For the Simulated Data Set		
	Gray	White	CSF
Gray	96.6	2.3	1.1
White	6.3	93	0.7
CSF	2.6	0.4	97

Table IV: Confusion matrix for the results of segmentation of the real MR brain images(15 slices) using similarity algorithm. Each row shows the % of each tissue which has been classified as every other tissue .

Tissue	Percent of Manual Segmentation classified by Similarity Measure Algorithm For the Real images		
	Gray	White	CSF
Gray	97	1.7	0.3
White	15.1	84	0.9
CSF	2	0	98

Table V: Confusion matrix for the results of segmentation of the real MR brain images(15 slices) using Fuzzy C-Means algorithm. Each row shows the % of each tissue which has been classified as every other tissue .

Tissue	Percent of Manual Segmentation classified by Fuzzy C-Means Algorithm For the Real images		
	Gray	White	CSF
Gray	88	12	0
White	1	99	0
CSF	1.3	0	98.7

Table VI: The computation time (using PC PII 333MHz,128MByteRAM) for segmentation of 256*256 MR brain image of 256 graylevels using Fuzzy Rule based, Fuzzy Similarity measures, and Fuzzy C-Means algorithms.

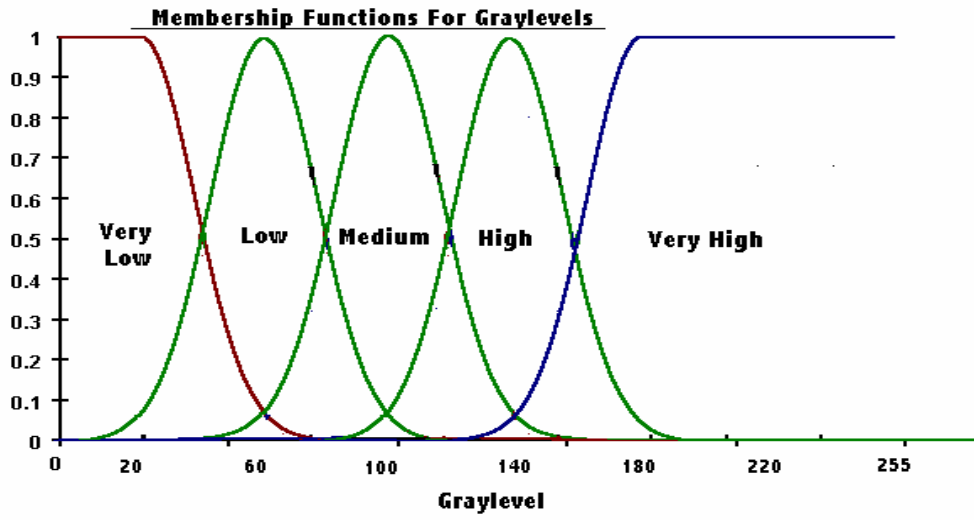| Segmentation Algorithms	Computational time(sec)
Fuzzy Rule Based System	0.05
Fuzzy Similarity Measures System	1.25
Fuzzy C-Means	0.4

Figure 1. Fuzzy membership functions for the 9 graylevels used in both algorithms
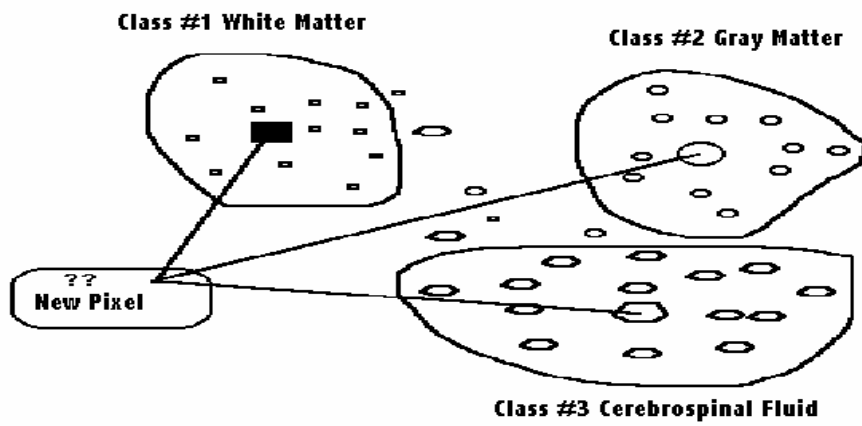

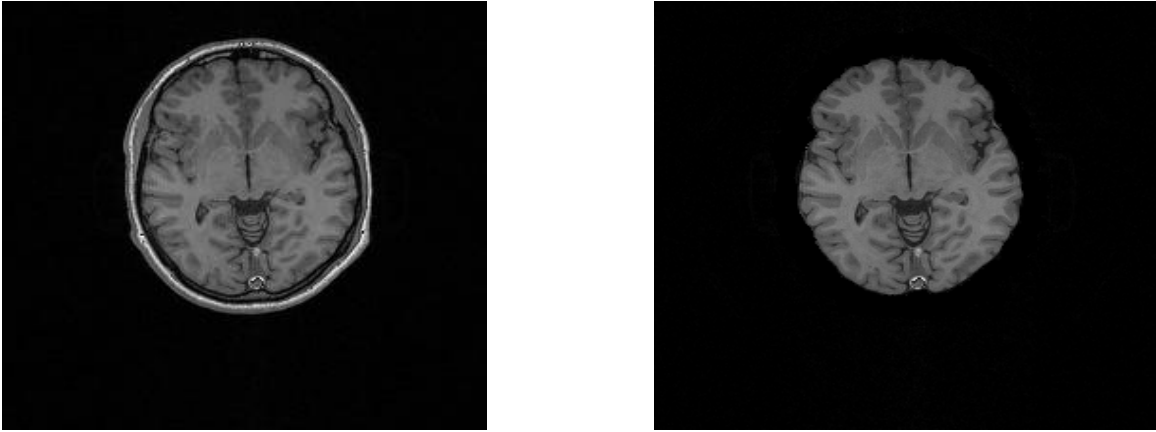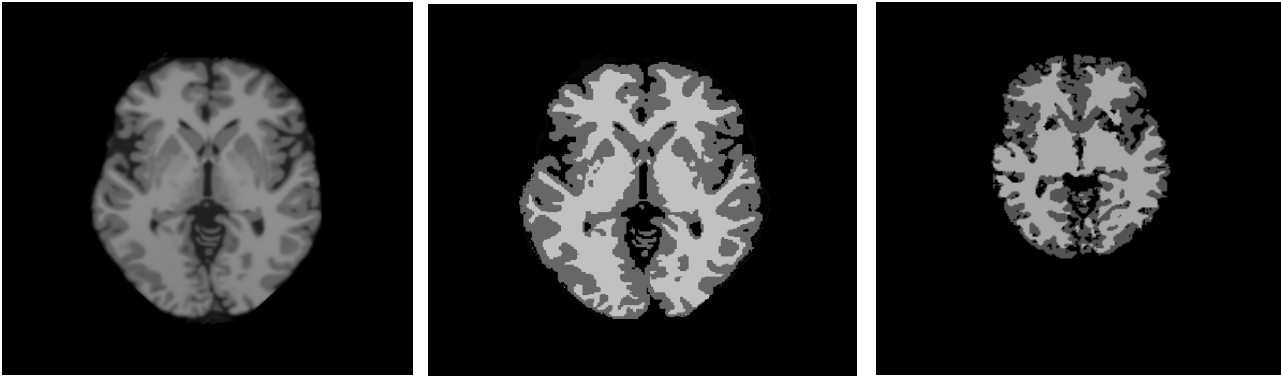Figure 2. Illustration of segmentation in the 9th dimensional space for the three classes

<center>(a)   (b)</center>
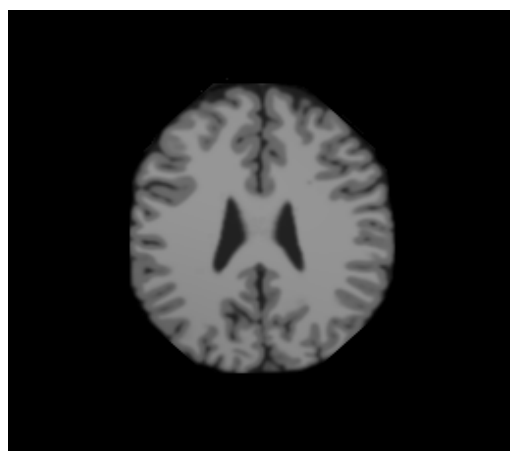
<center>Figure 3. (a) Original MR brain image and (b) image after preprocessing</center>

<center>(a)   (b)   (c)</center>

Figure 4. The results of segmentation using Fuzzy Rule-Based algorithm. (a) simulated image,(b) segmentation result of image (a), (c) segmentation result for image of Figure 3 (b)
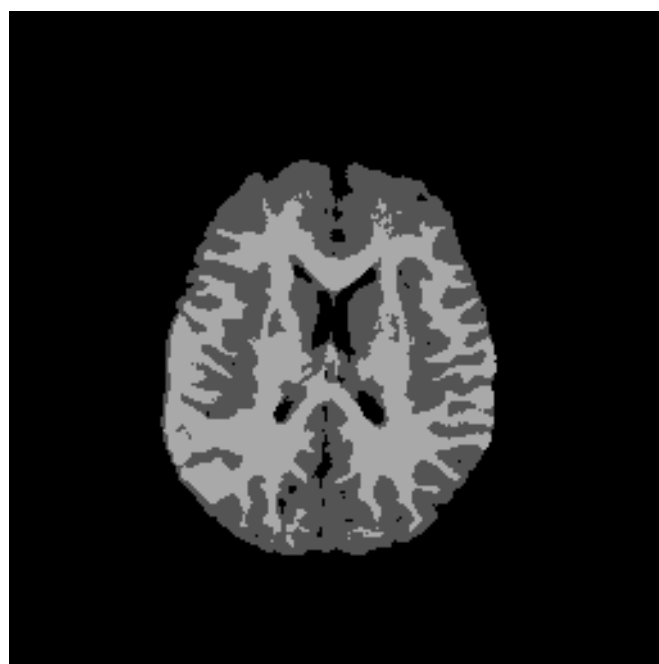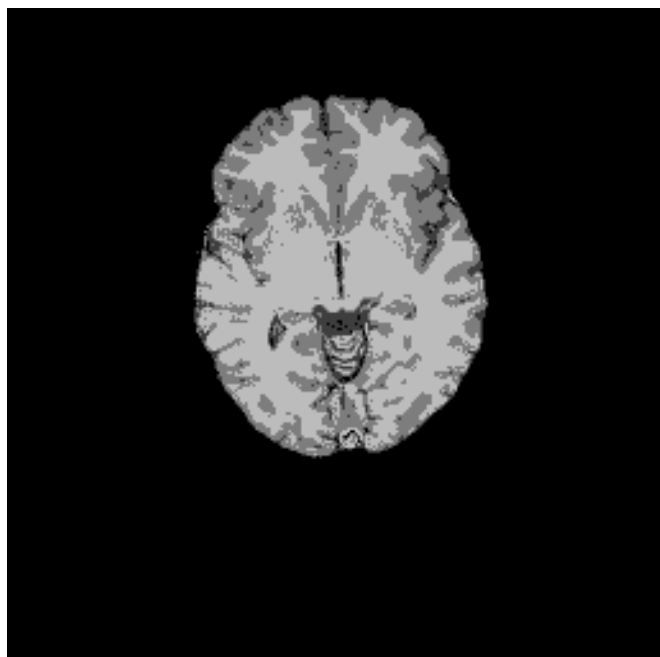
(a)

(b)

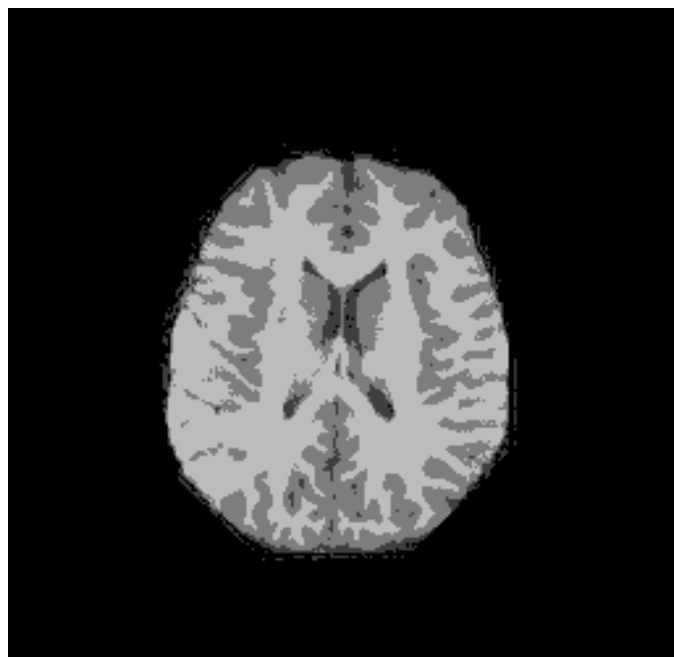©   (d)

Figure 5. The results of segmentation using Fuzzy Similarity measures algorithm. (a) simulated MR image, (b) segmentation results of image (a), (c) real image, and (d) segmentation results of image (c)

(a) (b)

Figure 6. The results of segmentation using Fuzzy C-Means algorithm (a) segmentation result of figure 3(b) and (b) segmentation result of Figure 5(c)