Fuzzy-Symbolic Analysis of MR Brain Images

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Abstract

This paper describes a hybrid of Fuzzy Set Theory and Symbolic Data Analysis to analyze the patterns extracted from real life application domain. In this research work we are considering the patterns extracted from Magnetic Resonance Brain Images for the analysis and we have confined the analysis of patterns to Feature extraction and Pattern classification. The main theme of this paper is to improve the classification accuracy with less computational time/memory and thus avoiding the usual trade-off between computational time/memory and classification accuracy. The proposed Fuzzy-Symbolic analysis comprises of Feature extraction, data reduction technique and Fuzzy classification using Symbolic Similarity distance membership function. To justify the results obtained by the proposed methodology, the results are verified and validated. Validation of the results are performed with new validation procedure namely modified Goodmann Kruskal Gamma (γ) Validation technique. Also performance of the proposed algorithm is compared and contrasted with the existing ones.

Keywords : Fuzzy Set Theory; Symbolic Data Analysis; Classification; Feature Extraction; Validation; MR Brain Images.

1. Introduction

In conventional data analysis, the objects are numerical vectors, the classification of such objects is achieved by maximizing intracluster similarity and minimizing intercluster similarity.

Symbolic objects are extensions of classical data types. In conventional data sets, the objects are 'individualized', whereas in Symbolic Data Sets, they are more 'unified' by means of relationships. Based on the complexity, the symbolic objects can be assertion, hoard or synthetic type[11,12]. The feature extracted to represent a pattern could be more complex and could be very much different from an ideal feature table, which generally is composed of n- dimensional feature vector of numeric attributes for every pattern. The description of features in such cases is more generic. Such objects/samples described in terms of generic pattern attributes are called Symbolic objects in the literature of Data Analysis [11, 12]

Fuzzy Set Theory provides a formal mathematical frame work in which vague conceptual phenomenon can be precisely and rigorously studied. The present work, hence has derived the advantages of Fuzzy Set Theory to combat the issue of uncertainty in Pattern Analysis [2,3,4].

From the above paragraphs it is evident that the two recent fields in Pattern Recognition(PR) namely, Fuzzy Data Analysis(FDA) and Symbolic Data Analysis(SDA) have been individually supplementary to the growth of PR, while seeming to have remained complementary to each other. Concrete research attempts have not been reported where the advantages of both SDA and FDA are grooved together in solving the more complex problems of Pattern Analysis. Thus the essence of this research paper is to fuse together the advantages of both FDA and SDA and its outcome is the development of a new problem solving strategy called Fuzzy-Symbolic Data Analysis(FSDA), which provides a new direction in the field of Pattern Analysis.

In this research work, we are considering the segmentation of Magnetic

Resonance(MR) Brain Images as a real life application. Analysis of Patterns extracted from MR Brain Images involves Feature Extraction, Data Reduction and Classification.

In this paper modifications are introduced in the existing Fuzzy Classification algorithms to handle symbolic data tables by employing some new concepts. In the proposed supervised classification, the training sets are learned by using the concept of Composite Symbolic Objects. The classification is performed using the training sets on the Patterns to be analyzed. Membership values for different classes are computed using the distance based membership function that makes use of the distance measure proposed by Gowda and Diday[12]. Many experiments are conducted to study the above classification model. In addition to the extensive experimentation implemented, we have carried out some validation tests to corroborate the accuracy of classification. Validation studies include modified Goodmann Kruskal Gamma validation technique, and Classification Accuracy Analysis.

2. Feature Extraction

In brain images obtained by Magnetic Resonance(MR) machine, segmentation/ classification using only intensity values is severely confined by field inhomogeneities, susceptibility artifacts and partial volume effects. Also, due to overlapping of gray values, the valley point in the gray level histogram is not deep. Hence, to overcome the above limitations the geometric properties of the image are considered. We are employing the feature extraction proposed by Zeheru chi et. al. [19]. Seven features are extracted from the pixels of an MR image of the brain, which include the pixel value, mean and standard deviation of pixel gray levels in a neighborhood of 3x3 pixels around each pixel, and edge intensities along the horizontal, vertical and two diagonal directions.

3. Transformation /Data Reduction

The merits of Symbolic Data Analysis have been instrumental in using the transformation technique(K. C. Gowda et. al. [13]) that transforms numerical data into Symbolic data, which in turn has been very useful in reducing computational time and memory space. This technique is based on the principles of $\propto$-cut technique in the Fuzzy Set Theory. As a prerequisite to the Fuzzy $\propto$ - cut technique, patterns extracted from Brain Images are Fuzzified using the ramp function. Fuzzy $\propto$ - cut technique performs data reduction by reducing the size of the input patterns and produces Symbolic objects as output. Each Symbolic object will be represented by a quantitative interval type of features.

4. Supervised Learning

Learning of Training Patterns for Magnetic Resonance Brain Images:

In MR brain image, the number of classes are known and we are interested in discriminating only three types of tissues present in the MR brain image, i.e., White Matter(WM), Gray Matter(GM) and Cerebro Spinal Fluid(CSF). Based on the human anatomy(Gerard J. Tortora et al.[10]) the training patterns for GM and WM are selected from the cortex region. The cortex region is composed mainly of two types of tissues GM and WM. GM forms the outer layer of the cortex, encasing the inner WM almost completely(Patrik et. al.[17]). The brain, as well as the rest of the central nervous system, is further protected against injury by the CSF. This fluid circulates through the subarachnoid space around the brain and spinal cord and through the ventricles of the brain. The training pattern for the CSF is selected from the subarachnoid space or from the ventricle region.

The patterns or pixels around the seed pattern selected from each class prototype for training in magnetic resonance image are considered for the formation of a training set and are merged to represent the class prototype. The patterns are merged as explained in Section 5 to form the Composite Symbolic Objects. Considering the neighboring pixels around the seed pattern selected for training helps to reduce the misclassification rate. This strengthens the training set as it takes care of intra class variations.

5. Composite Symbolic Object

Merging is the process of gathering two objects together based on the proximity measures and assigning them the same cluster membership, or label for further clustering. In Symbolic Data Analysis, the concept of Composite Symbolic objects(CSO) is used to describe a newly formed object from the merger of two Symbolic objects. We are employing the concept of forming CSO as proposed by Gowda and Diday[11]. Computational details of forming CSO are as follows:

The composite object resulting from two Symbolic objects

$A = A_1 \times A_2 \ldots A_d$, $B = B_1 \times B_2 \ldots B_d$ is:

$$C = A \oplus B = (A_1 \oplus B_1) \times (A_2 \oplus B_2) \times \ldots \times (A_d \oplus B_d) \qquad \langle 1 \rangle$$

where $\oplus$ is a Cartesian join operator.

When the k-th feature is quantitative, $A_k \oplus B_k$ is defined as the minimum interval that includes both $A_{k \text{ and }} B_{k.}$ That is,

$A_k \oplus B_k = [\min(a_{kL}, b_{kL}), \max(a_{kU}, a_{kU})]$

where $a_{kL,}a_{kU,}$ and b_{kL}, b_{kU} stand for the lower and upper bounds of A_k and B_k respectively and for quantitative ratio/absolute type $a_{kL}= a_{ku}$ and $b_{kL} = b_{kU.}$ When the k-th feature is a qualitative nominal, $A_k \oplus B_k$ is the union of A_k, B_k

$A_k \oplus B_k = A_k \cup B_k$

6. Similarity Distance Membership Function

In a fuzzy representation, the training set is defined as a fuzzy set and each Symbolic object is represented as a Set element. An excellent review of the use of Fuzzy set theory in classification/clustering using membership function can be found in J. C. Dunn[7,8]; James C. Bezdek [2,3]. Choosing a membership function is the first step and an essential one for fuzzy logic applications. The choice of membership function is usually problem dependent, and this is often decided heuristically and subjectively (Zehru Chi et al.[19]. We have used a distance based membership function that reflects the degree of proximities from a pattern to a set of patterns in a data set. The distance membership function gives the degree of membership values between the set elements and the different fuzzy sets. The computation of membership values using a distance based membership function is as follows:

Let $\{Y_1, Y_2, Y_3 \ldots Y_n\}$ be a set of n Symbolic objects in d dimensions and $\{T_1, T_2 \ldots T_c\}$ be a training set of C class prototypes in d dimensions.

$$\mu_{ij} = \frac{S(Y_i, T_j)^{\frac{2.0}{m-1}}}{\sum_{k=1}^{c} S(Y_i, T_k)^{\frac{2.0}{m-1}}} \qquad \textbf{<2>}$$

$2 \le j \le C, \; 0 \le i \le n,$

$\mu_{ij} \Rightarrow [0, 1]$, m = Fuzzifier constant, and is selected as n/n-2,
C = number of classes present in the data.
n = number of Symbolic objects.

S(Y, T) is the Symbolic Similarity measure between Symbolic object Y and Composite Symbolic object T. The Similarity measure S(Y, T) is computed using the distance Measure proposed Gowda and Didey[11].

7. Supervised Classification

Fuzzy classification imposes Fuzzy partitions on the data space Y, i.e., the membership of each vector y in Y is divided among C classes. In many applications, the Fuzzy partition of the given pattern must be further processed, to obtain a crisp partition. If the nature of the problem is such that a crisp classification must be the final output, a defuzzification procedure should follow the Fuzzy classification. Two equivalent approaches given by Menaham Friedman and Abraham Kandel [15] are:

i). Maximum membership classifier.
ii). Nearest center classifier.

To obtain the classification color map and to find the recognition rate we have employed the maximum membership classifier.

Maximum Membership Classifier:

The idea here is to make the least ambiguous assignment of membership values over Y consistent with the condition that any two vectors with membership values near unity in the same class should be more alike than any other pair of vectors with membership values near unity in different classes. When Y has a pronounced class structure, the degree of equivocation or partition fuzziness, should be minimal; more precisely, all y's within the same cluster should receive membership values near unity in the same class and substantial divisions of membership should occur only for a relatively small percentage of in between cases(e.g., noise and bridge points) (J. C. Dunn [2]; Menahem Frieman et al.[15]).

7.1. Computational Algorithm for Fuzzy-Symbolic Supervised Classification

The algorithm comprising of three passes, is given below:

Pass #1: Preparing the patterns under consideration for the classification.

1. Extract the patterns from the image under consideration. Let the number of patterns be m.

2. Depending on the type of pattern, extract/select the corresponding features as described in Section 2.

3. Fuzzify the extracted/selected features (Section 3)

4. Convert the fuzzified patterns into Symbolic Objects by using Fuzzy ∝-cut technique(Section 3).

Pass # 2: The training set is selected in this pass

5. Depending on the type of image, select a training set from extracted/ selected feature vectors (Section 4)

6. Select the training set for all 'C' specific classes.

7. Determine the 'C' number of Symbolic training patterns by repeating the steps 3 and 4 from the established training information.

Pass # 3: The initial 'n' number of patterns are classified into 'C' number of classes during this pass.

8. Begin with 'C' number of symbolic training patterns and 'n' number of patterns.

9. For i=1 to n, perform steps 10 to 13.

10. For j = 1 to C, compute the degree of belongingness of the 'i' th pattern to the 'j' th symbolic training pattern.(Section 6)

11. For preparing classification map, classify the pattern i by assigning it to the Symbolic training pattern having the highest membership value.

12. For the computation of statistical results, consider the partial membership values of patterns with respect to different Symbolic training patterns.

13. Store the information about the statistical results and the classification maps.

The reference numbers assigned during data reduction(Section 3) to the original patterns of size 'm' are used for the preparation of the classification map and for the final computation of statistical results.

8. Validation

Modified Goodman-Kruskal Gamma Validation for Fuzzy Partition:

Cluster validation refers to procedures that evaluate the results of cluster analysis or unsupervised classification in a quantitative and objective fashion. In other words, cluster validation is used to compute one measure of global fit between the original proximity or distance matrix and the resulting classification. Frequently used validation methods are Hubert's Tau(τ)statistics and Goodman Kruskal Gamma(γ)statistics. Both are described in detail by Anil K. Jain and Dubes[1].

Hubert's Tau (τ) statistics is a point correlation technique and measures the degree of linear correspondence between pattern distance matrix and pattern category label matrix. In Hubert's Tau (τ) statistics validation method the experiment has to be repeated several times to obtain a realistic validation index and hence is suitable for data sets with a small number of patterns, whereas Goodman Kruskal Gamma(γ) validation method is comparatively simpler and need not be repeated several times to obtain validation index. Hence, Goodman Kruskal Gamma validation takes less computational time when compared to τ statistics.

The conventional Goodman Kruskal Gamma described in Anil K. Jain and Dubes [1] is for crisp partition. The Goodman-Kruskal Gamma(γ) statistics measures the rank correlation between two sequences of numbers. These sequences of numbers can be obtained from the proximity matrix and the pattern category label matrix. The basic idea behind this statistics is given below.

Let $X = \{x_1, x_2, \ldots, x_M\}$ be the pattern distance matrix of $M = m(m-1)/2$ patterns, and $Y = \{y_1, y_2, \ldots, y_M\}$ be the pattern category label matrix of m(m-1)/2 patterns.

A pair is a set of doublets taken from the corresponding positions in the two sequences, one doublet from X and the other from Y. A doublet is a pair of numbers from one of the sequences, either X or Y. The γ statistics measures the degree of association between the two sequences in terms of the number of concordant (S_+), and discordant(S_-) pairs.

The pairs of doublets $\{(x_i, x_j), (y_i, y_j)\}$ are concordant if either of the conditions ($x_i < x_j$ and $y_i < y_j$) or ($x_i > x_j$ and $y_i > y_j$) is true. The pairs are discordant if either of the conditions ($x_i < x_j$ and $y_i > y_j$) or ($x_i > x_j$ and $y_i < y_j$) is true. The pairs are neither concordant nor discordant if ($x_i = x_j$)or($y_i = y_j$).

Then, the γ statistics is computed as

$$\gamma = \frac{S_+ - S_-}{S_+ + S_-} \qquad \textbf{<3>}$$

As is evident from the above equation, the γ value varies between -1 and 1. The γ value near 1 indicates a strong relation between the two sequences with one sequence increasing along with the other one. A value near -1 also indicates a strong correlation between the two sequences, where, as one sequence increases, the other one decreases. A value near 0 indicates no relationship between the sequence.

The Supervised classification algorithm presented in Section 7.1 produce Fuzzy Partition. The conventional Goodman Kruskal Gamma Validation technique fails to handle Fuzzy Partition. Hence, in this chapter we are proposing a modified Goodman Kruskal Gamma validation technique to handle Fuzzy Partition. In the proposed method, during the computation of concordant and discordant pairs we use the membership value unlike the category label which is 0 or 1. The details of the computation are given in Scetion X.

The Goodman Kruskal Gamma Validation method invariably involves computations of the distance matrix, membership values, and category labels. This requires a huge amount of memory and computational time for image data. To avoid the requirement of huge memory and computational time, we use the Proportionate Sampling method for image data proposed by Srikanta Prakash et al. [18].

8.1. Computational Algorithm of Modified Goodman Kruskal Gamma Validation

1. Let the number of Clusters/Classes present in the data set be C.

2. Classify the patterns with different clusters and store the class labels(Y) along with corresponding membership values(M).

3. From each cluster select a fixed percentage of samples of size n[18].

4. Compute the distance matrix(X) from the selected representative patterns.

5. Make i=1; j=1; k=1; $S_+ = 0$; $S_- = 0$.

6. Select three pairs of doublets, first pair of doublets from X, second pair of doublets fromY and the third pair of doublets from M. All the doublets are taken from corresponding positions with respect to a particular cluster k.

7. Compute the concordant(S_+) and the discordant(S_-) pairs as follows:

If {(y_i _ y_j) or (x_i _ x_j)}
Then
{
If{[($x_i < x_j$) and ($m_i < m_j$)]or [($x_i > x_j$) and ($m_i > m_j$)]}
Then increment S_+
Else
{
If{[($x_i > x_j$) and ($m_i < m_j$)]or [($x_i < x_j$) and ($m_i > m_j$)]} Then
increment S_-
}
}
Else { Pairs are neither concordant nor discordant. }

8. Compute the level of significance with respect to a particular cluster as:

$$\gamma_k = \frac{S_+ - S_-}{S_+ + S_-}$$

9. If(i = n and j = n) Go to Step 9, Else[make { i = i+1; j = j+1} Go to Step 5].

10. If (k<C) Then { Make [k = k+1; i =1; j =1; $S_+ = 0$; $S_- = 0$] Go to Step 5 } Else Go to Step 11.

11. Compute the overall level of significance as:

$$\gamma_k = \sum_{k=1}^{c} \frac{\gamma_k}{C} \qquad \textbf{<4>}$$

9 Verification

To Verify the results obtained by the proposed method we have used some well known methodologies such as, Confusion Matrix , Producer's Accuracy, User's Accuracy found in Mather [14] and Kappa Statistics, Overall Classification Accuracy, Expected Classification Accuracy found in Congalton [3].

10. Experimentation and Validation

Experiment with MR Brain Image Data for Segmentation of Different Tissues Through Classification:

The Magnetic Resonance(MR) brain image in Sagittal section is considered for the experiment. Characterization of brain tissues in MR brain image is useful for some medical diagnostic procedures. In this experiment we have classified the MR brain image pixel(Pattern) into several meaningful categories, like background of the image and three types of brain tissues(White Matter, Gray Matter and Cerebro Spinal Fluid(CSF)). The segmented images obtained by the proposed algorithm are shown in Fig. 1. We find that All the three types of tissues are well discriminated. Fig. 2 shows the percentages of area covered by different tissues and background.

For further authenticity in the segmentation of WM, GM and CSF, the MR simulation data of a brain phantom is utilized. The simulated Pseudo-T1 MR brain image was provided by the PET center, Minneapolis Veterans Affairs Medical Center at their web site http://pet.med.va.gov.:8080/demos/segment.html. The advantages in using this data set is the availability of the Tissues truth information. The proposed algorithm is applied on the Segemented Pseudo MR brain image is shown in Fig. 3. The results of the performance evaluation test by the proposed method is tabulated in 2. The validation results show the level of significance as 1.0 with the computational time of 10 Seconds.

11. Relation to Other Works

Segmentation/classification of different tissues using intensity based methods and edge based approaches in MR brain imaging suffer from spurious edges, strong variations in edge strengths and local gaps in edges. Classification methods and region based methods suffer from the fact that there is a significant overlap in intensity between different tissue types, owing to Radio Frequency(RF) coil inhomogeneity, susceptibility artifacts and partial volume effects. To compensate retrospectively for RF induced variations a number of approaches have been proposed, but none of these is widely applicable(Niessen et al. [16]).

The proposed algorithm overcomes the above mentioned drawbacks in the following ways:

i). During feature extraction, edge dependent smoothing technique is used to preserve the boundaries between tissues.

ii). To take care of intensity inhomogeneities, the overlaps are solved by considering the fuzzy membership values

iii). Training fields for three types of tissues are formed with the help of a brain atlas and training fields are represented as CSO that result in strengthening of training field for intra class variations.

Further, Fuzzy c Means(FCM) and the proposed algorithm are applied on the Pseudo MR brain image. The proposed algorithm took 10 seconds while the FCM took 39 seconds for the computation. Also validation studies showed the level of significance as 1.0 for the proposed method and 0.963 for FCM algorithm. Due to the Fuzzy-Symbolic analysis, a good improvement in the classification accuracy is found. The details about the classification accuracy of the proposed and FCM method are tabulated in Table 2.

12. Summary

A hybrid of the Fuzzy-Symbolic Supervised classifier is proposed for classifying patterns extracted from MR brain images. Incorporation of pattern partial membership and consideration of intra class variations in the training set selection help to improve the overall classification accuracy of the proposed algorithm. Also the proposed algorithm takes less computational time and memory due to the application of the data reduction technique.

To justify the superiority of the proposed algorithm it is compared and contrasted with some existing methods, and the classification results are validated using the modified Goodmann Kruskal Gamma(γ) validation technique.

14. Reference

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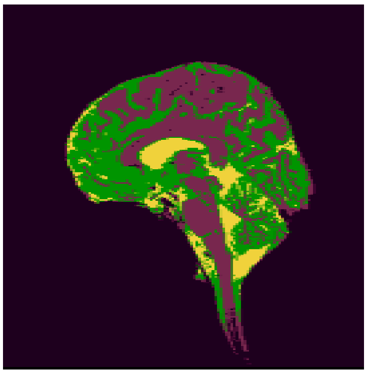

Figure 1 Classification Map of MR Brain Image – Proposed Fuzzy Supervised Classification

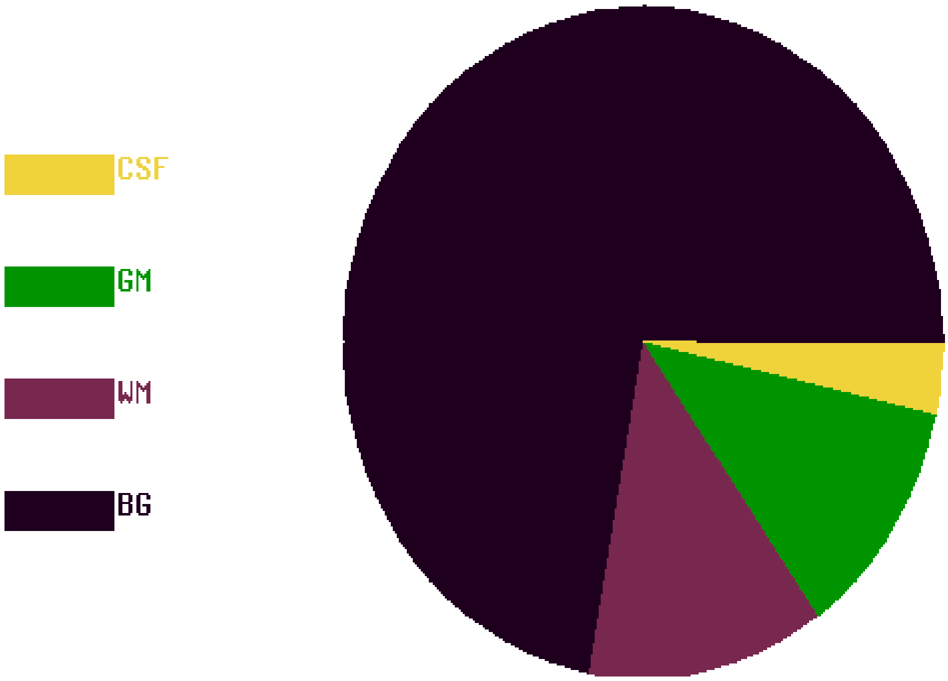

Figure 2 Pie Chart showing the Different tissues in MR Brain Image – Proposed Fuzzy Supervised Classification

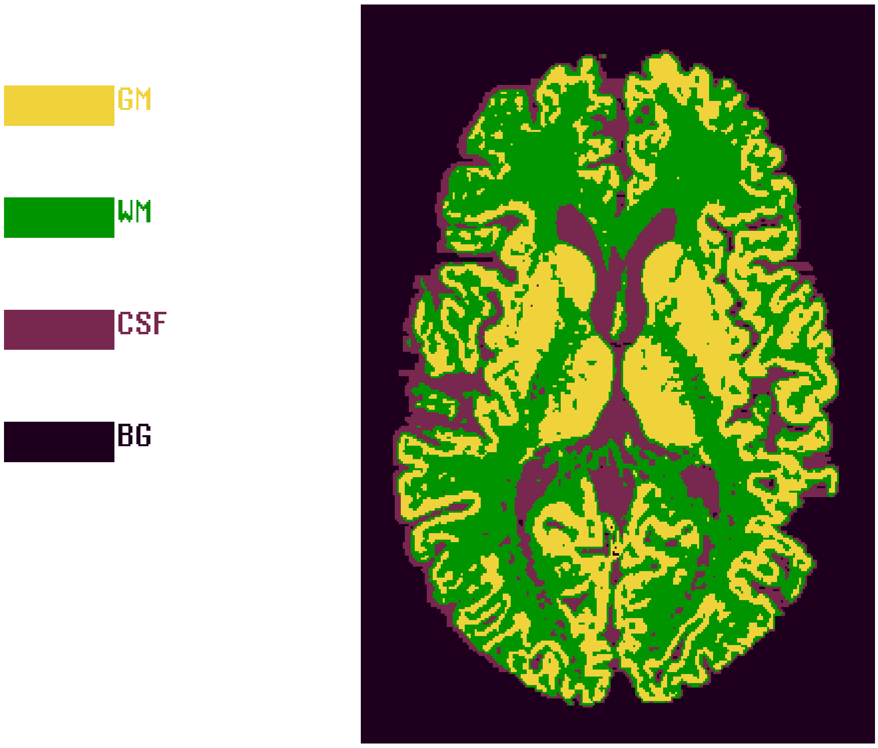

Figure 3a Classification Map of Pseudo MR Brain Image
– Proposed Fuzzy Supervised Classification Method

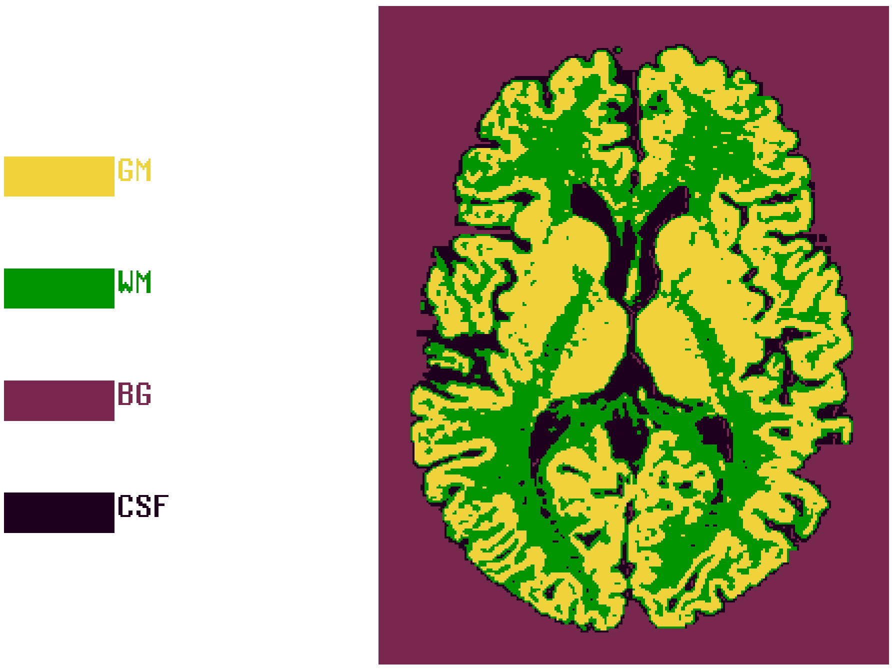

Figure 3b Classification Map of Pseudo MR Brain Image
- Fuzzy C-Means Classification Method

Table 1. Confusion Matrix of Pseudo MR Brain Image

Proposed Fuzzy Supervised classifier Data set : Pseudo Magnetic Resonance Image(Brain); No. of classes: 4					
Predicted cover type	Reference data (“ground truth)				
Class	**1**	**2**	**3**	**4**	**Row totals**
1	10	0	0	0	10
2	0	10	0	0	10
3	1	0	9	0	10
4	0	0	0	10	10
Column totals	11	10	9	10	40

Table 2. Performance Evaluation of Classification Methods on
Pseudo MR Image

Data set: Pseudo Magnetic Resonance Image(Brain) **Size: 258X 332** **No. of classes: 4**							
Classification methods	**PA %**	**UA %**	**OCA %**	**ECA %**	**KHAT %**	**Gamma Value**	**Computational Time**
Proposed classifier	C1= 90.09 C2 = 100 C3 = 100 C4 = 100	c1 = 100 c2 = 100 c3 = 90 c4 = 100	97.5	25	96.66	1.0	10 Sec
FCM - Method	C1 = 83.33 C2 = 90 C3 = 100 C4 = 100	c1 = 100 c2 = 90 c3 = 90 c4 = 100	95	25	93.33	0.963	39 Sec
Note : OCA – Overall Classification Accuracy; PA - Producer’s Accuracy; ECA – Expected Classification Accuracy; UA - User’s Accuracy; KHAT – Kappa Statistic; Gamma Value - Goodman Kruskal Gamma Validation;							