EFFECTIVE SEGMENTATION OF WHITE MATTER LESION BASED ON ROUGHSET THEORY AND FUZZY CLUSTERING

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Abstract--Magnetic Resonance Imaging (MRI) is the state of art medical imaging technology that captures cross sectional view of the brain. Fluid Attenuation Inversion Recovery-FLAIR MRI is a pulse sequence used in MRI and together with T1, T2& PD images. The volume of White Matter Lesion (WML) is measured using Partial Volume Averaging (PVA) artifact. Change in white matter is related to carotid disease and chance of occurrence of stroke and related diseases can be predicted with subvoxel precision by volumetric analysis. To improve the quality of Segmentation of WML Multiple Kernel Fuzzy-C Means clustering (MKFCM) with rough set theory is used in the proposed work. Rough set theory is introduced with fuzzy classifier for obtaining better solution. Automatic segmentation is efficient and reliable than manual segmentation. The major advantage is the exact identification and diagnosis the related disease at the initial state.

Index Terms—MRI image, FLAIR MRI, White Matter Lesion (WML), Partial Volume Averaging (PVA), Multiple Kernel Fuzzy C means (MKFCM), Rough set Theory

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INTRODUCTION

The human brain is classified into White Matter, Gray Matter and Cerebrospinal Fluid. Magnetic Resonance Imaging (MRI) or Nuclear MRI (NMRI) is primarily a medical imaging technique most commonly used in radiology to visualize the internal structure and function of human brain. MRI uses powerful magnetic field to align the nuclear magnetization of hydrogen atoms in water in the body.

FLAIR MRI is related to the cerebrospinal fluid in the brain. The normal volume of CSF is 150 mL. Due to emotional and other action this volume changes and maximum of 500mL is permissible. Above that rate is treated as abnormality. By calculating the volume of CSF the changes can be predicted.

The study of volume of white matter is very important in the current days, because the stroke and carotid disease are the third cause for death in the world according the stroke statistics. The blocks in the supply of blood to the brain vascular accident, or cause cerebral stroke. Because of stroke significant neurological defects occurs that leads to various physical impairments such as sensory motor paralysis, loss of sensation, as well as difficulties in interpreting spatial relationships [1]; stroke can also be fatal. By calculating the volume of white matter in the brain, the stroke, blood pressure, hyper tension such diseases can be diagnosed at the initial stage. White matter is the amount of dead cell present in the brain. Manual segmentation of white matter lesion is more complex and error prone.

Lesion is the change in abnormalities in white matter. FLAIR images have similar tissue contrasts as T2-weighted MRI; the difference is the presence of cerebrospinal fluid (CSF) signal and is nulled for enhanced discrimination of ischemic pathology [4]. In FLAIR MRI, WML appear as hyper intense objects scattered throughout the white matter. Using the FLAIR images, lesions were outlined and the volumes were found based on the number of pixels in the region. The volumes of these lesions [lesion load (LL)] were important in determining their relationship to stroke.

White matter is present in both the hemisphere of our brain. The left part of brain controls the right side of the body and right brain controls the left part of the body. For normal condition both the hemisphere contains equal volume. If any deviation in both regions occurs, then it is treated as abnormality. The difference is taken and according to that the percentage of occurrence of disease can be estimated.

To combine the different datasets T1 weighted, T2 weighted, Proton Density and FLAIR images are fused using Fuzzy clustering. The proposed work uses Multiple Kernel Fuzzy C Means clustering and rough set theory is used. C means clustering is widely used because of its simplicity and fast convergence. Kernel FCM is the advanced technique which maps the original image into higher dimensional image. Fuzzy membership functions are easy to implement and they improve speed of inference engines.

Human reasoning can be emulated using fuzzy logic. Fuzzy logic is proved to be a powerful tool to handle and process noisy and vague data. Fuzzy rules are more flexible than crisp rules for many reasons. Clustering based segmentation includes the spatial information for better performance. Clustering means the selection of input features such as pixel colour, intensity, texture or weighted combination of other i/p features. Kernel is a weighting function used in non parametric techniques and also used to estimate the random variable density. Multiple KFCM fuses information from various sources from different dataset and obtains exact volumetric analysis.

Several rough set-based and fuzzy-based methods have been proposed in various field. These methods are very efficient in large data sets and may be adaptable for real-time applications. Membership functions of fuzzy sets were generated from the product space of the selected features. Also, the selected features from PCA-ICA phase suffered from data inconsistency which degraded the fuzzy classifier performance. It is an integration of PCA, ICA, Rough Set, and fuzzy classifier to identify and label suspicious regions from white matter lesion or edema . PCA is an orthogonal transform and a decorrelation technique that captures maximum variance. The correlation between components of a vector is used to measure data redundancy. ICA is a statistical technique that can be used to extract hidden features within a set of data.

1. METHODOLOGY

The parameter γ indicates the amount of tissue present in a voxel. PVA quantification is generally an estimation problem, where the variable γ is sought. Traditional techniques for normal T1 or T2 MRI search for a global estimate of this parameter, i.e., $\gamma(x)$, that quantifies the proportion of one tissue present in a voxel of intensity x. Moreover, neurological MRI often has

non-Gaussian or unknown noise properties, causing techniques that rely on normality to be inaccurate. To combat these downfalls, the present study focuses on a non-statistical, image-based PVA modelling approach for robust segmentation of WML in FLAIR. The following methods are used.

A. PVA Model

PVA produces an image intensity that is linearly dependant on the proportion of each tissue in the voxel. In neuro MRI, where two tissue types mix per PVA voxel , the intensities of these mixels,1 $Y_{jk}(\mathbf{y})$, are determined by the proportion of the first tissue i, in comparison to that of the second tissue j, as in

$$X_{ij}(\mathbf{y}) = \gamma(\mathbf{y}) \cdot Xi(\mathbf{y}) + (1 - \gamma(\mathbf{y})) \cdot X_j(\mathbf{y}) \qquad (1)$$

Where $Xi(\mathbf{y})$ is the intensity value from first tissue's intensity distribution pi(y) at spatial location $\mathbf{x} = (y1, y2) \in Z2$, $X_j(\mathbf{y})$ is the intensity of the second tissue $\sim p_j(x)$, and $\gamma \in [0, 1]$ is the proportion of tissue *j* present at **y** (the remainder of the voxel is a fraction of tissue j, i.e., $1 - \gamma$). Using this mathematical relationship that describes PVA in terms of the intensities of mixtures voxels quantification of PVA in a new way based on the edge content of the image. Tissue intensities are simulated as constant quantities $Xi = Ii$ and γ is deterministic.

In the context of WML segmentation in FLAIR MRI using the ideal signal model, there are three pure tissue classes which are simulated as constant quantities:

1) CSF, $X3 = I3$;

2) Gray matter (GM) AND white matter (WM) 2, $x2 = I2$;

3) WML, $X1 = I1$;

Which, when applied to (1), results in an idealized multiclass PVA model

$$X12(\mathbf{y}) = \gamma 12(\mathbf{y}) \cdot I1 + (1 - \gamma 12(\mathbf{y})) \cdot I2 \qquad (2)$$

$$X23(\mathbf{y}) = \gamma 23(\mathbf{y}) \cdot I2 + (1 - \gamma 23(\mathbf{y})) \cdot I3 \qquad (3)$$

whereX12(**y**) and X23(**y**) are the intensities of PVA voxels in the WML-brain and brain-CSF boundaries, respectively. The brightest tissue (WML) is denoted by $I1$, where $I1 > I2 > I3 \geq 0$.

The parameter γ_{12} describes what percentage of the voxel is made up of WML and quantification is required for noise free WML volume computation. Finding an image-based estimate for γ would be of great value.

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B. *Edge-Based PVA Modelling*

Consider the ideal signal model of (2) and (3) to examine the edge content in the PVA regions. The gradient of these equations are given by

$$X'_{12} = \gamma'_{12} \cdot (I1 - I2), X'_{23} = \gamma'_{23} \cdot (I_2 - I_3) \quad (4)$$

Where γ' is the change in the proportion of tissues parameter. Solving for γ' results in two PVA quantifiers

$$\square'_{12} = \frac{X'_{12}}{I_1 - I_2}, \square'_{23} = \frac{X'_{23}}{I_2 - I_3} \quad (5)$$

By using these equations each PVA measure γ'_{ij} is a normalized. It is a normalized representation because the largest possible value of X'_{ij} is $I_i - I_j$ and the minimum is 0 in a constant region, resulting in $0 \leq \gamma'_{ij} \leq 1$.The study focuses on an edge-based estimate for $\gamma'$and uses it to decode the proportion of tissues parameter γ, since these class-specific variables describe PVA in terms of the gradient.

C. *Fuzzy Edge Model*

A fuzzy technique based on the cumulative distribution function (CDF) of the gradient [19], [20], is employed to estimate $\gamma'(\mathbf{y})$.To computes this metric, the traditional magnitude of the gradient, i.e., g, is first estimated by

$$g = ||\nabla y|| = \sqrt{\left(\frac{\delta y}{\delta x1}\right)^2 + \left(\frac{\delta y}{\delta x2}\right)^2} \quad (6)$$

Where the Sobel operator is used. The probability distribution function (PDF) of the gradient $p_G(g)$ is computed further, and based on this PDF, the CDF of the gradient magnitude is found and used as an estimate for the edge information in the image

$\gamma'(g) = \text{Prob}(G \leq g) = \sum_{k=0}^{g} pG(k)$ (7)

where $\gamma'(g) \in [0, 1]$.

This nonlinear fuzzification of the edge information quantifies the "certainty of edge presence."This parameter is expressed as a function of the gradient that to be used to approximate $\gamma'(y)$, $\gamma'(g)$ is mapped back to the spatial domain: $\gamma'(g) \rightarrow \gamma'(y)$.This fuzzy edge measure provides large and similar values to significant edges as shown in [19] and [21]. It groups significant edges, while suppressing the irrelevant ones. The normalized value, i.e., $0 \leq \gamma'(y) \leq 1$; that representative of the edge information in the image, it is used to represent PVA in the image. Although such a nonlinear mapping function localizes PVA in the ideal images and demonstrates the motivation for an edge based approach, because of the local nature of the gradient operator, noise severely degrades its performance in noisy images. Since MRI are inherently noisy, a new estimate based on the global edge content is utilized instead of the localized metric $\gamma'(y)$, which is susceptible to noise.

D. Multiple-kernel fuzzy c-means algorithm together with Rough set Theory

The application of multiple or composite kernels in the FKCM has its advantages. In addition to the flexibility in selecting kernel functions, it also offers a new approach to combine different information from multiple heterogeneous or homogeneous sources in the kernel space. Specifically, in image-segmentation problems, the input data involve properties of image pixels sometimes derived from very different sources. Therefore, can be define different kernel functions purposely for the intensity information and the texture information separately, and we then combine these kernel functions and apply the composite kernel in MKFCM to obtain better image-segmentation results. Examples that are more visible could be found from multitemporal remote sensing images. The pixel information in these images inherits from different temporal sensors.

i) Training Phase Using PCA-ICA.

A training matrix $P_{trainN\times M}$ is constructed by placing training sub images as rows in the matrix where *N* represents number of training sub images and *M* represents size of each square sub images. PCA algorithm is used to reduce its dimensionality. A minimum square error approximation of the training matrix $P_{trainN\times M}$ can be found using the following equation

$$X_{re}=P_{train\ N\times M}P_{M\times V}\,P^{t}_{M\times V} \approx P_{train\ M\times V} \qquad (8)$$

The extracted features from the corresponding training set are estimated using

ii) *Testing Phase Using PCA-ICA.*

First, a testing matrix $P_{testN\times M}$ is constructed, where each testing sub image forms a row in the matrix. Second, its rows are normalized by their mean. Third, The regions in $P_{testN\times M}$ are projected on the reduced data from the training procedure using

$$Q_{trainN\times V} = P^{r}_{N\times V}W^{-1}_{V\times V} \qquad (9)$$

The reduced dimensionality extracted features from the corresponding testing set are estimated using the equation

$$Q_{testN\times V} = Q_{tN\times V}W^{-1}_{V\times V} \qquad (10)$$

iii) Rough Set Model.

There are some inconsistent elements in the proposed matrices $Q_{trainN\times V}$ and $Q_{testN\times V}$. These elements have same selected features but belong to different classes. To cause inconsistency and thus improve classification results, Rough Set Reduction is used as a subset selection. The proposed training framework can be represented as

(1)The consistent elements from the training matrix are removed. The resulting matrix is $Q_{trainNN\times V}$, where NN < *N*.

(2) Construct the decision matrix, INN× (*v*+1) = [*Q*train*NN*×*vDNN*×1], where *Q* contains the condition attributes (selected features from PCA-ICA phase) and *D* is the decision attribute.

(3) Find the Core attributes using the following procedure

(i) Initialize Core vector into *Ø.*

(ii) Check the cardinality for each attribute

(4) Find Reduct attributes by suitable methods.

iv) Testing Phase

In this step, features are selected from the matrix $Q_{testN\times V}$ in the same order they were selected from $Q_{trainN\times V}$ during the training phase. Finally, $Q_{trainN\times VV}$ and $Q_{testN\times VV}$ are reconstructed with selected Reduct features while dispensable features are thrown away.

v) Fuzzy Classifier.

Two single fuzzy if-then rules are used here to represent the normal and abnormal fuzzy sets. The membership functions of each antecedent fuzzy set are aggregated using the information about the selected feature values of the training sub images.

The proposed fuzzy-based classification algorithm can be summarized as follows:

(1) Two activation functions $\mu asN\times 1$ and $\mu nsN\times 1$ are initialized to 0 where each element of them represents the aggregated membership functions of the selected feature values for the corresponding testing subimage.

These parameters are defined as.

- $\mu ask\times 1$ represents the membership degree of the kth testing subimage to the fuzzy set abnormal.
- $\mu nsk\times 1$ represents the membership degree of the kth testing subimage to the fuzzy set normal where

$1 \le k \le N$.

(2) Using (11), membership functions of fuzzy sets of the testing subimages are obtained from the mean and standard deviation of their selected features based on the information from the selected feature values of the training subimages:

$$U_{ij}(x_{ij})=\exp\left(-\frac{(x_j-\mu_j)^2}{2(\sigma_j)^2}\right) \qquad (11)$$

where μj represents mean of all samples of the current selected feature xj , σj represents their standard deviation, and i is an index for the selected features from the training phase.

(3) The membership functions are normalized using

$$U_{ij}(x_j) = \frac{U_{ij}(x_j)}{max_{ij}(U_j(x_j))} \qquad (12)$$

(4)The membership functions are aggregated using (13) to find the degree of activation of each fuzzy set where *i* is an index for the selected features from the testing phase:

$$\mu_i(x) = \sum_{j=1}^{N} U_{ij}(x_j) \qquad (13)$$

(5) By assigning the corresponding testing subimage into the fuzzy set with the maximum degree of activation, a crisp decision is made, that is, normal or abnormal. Equation (14) is used for this purpose where *Y* is used as an index of a testing subimage being identified as normal or abnormal:

$$Y=\max\left(\mu_{us}(x),\mu_{ns}(x)\right) \qquad (14)$$

E. WML Segmentation

As the PVA map $\gamma(x)$ dictates how tissue classes are mixing, it can be easily modified to get class membership function for the WML. Since a value of $\gamma 12(x) > 0.5$ indicates that tissue (WML) is dominating at this gray level, this point is used to define where the class membership becomes more in favour of WML. If x2 and *x*1 denote the starting and ending gray level values for $\gamma 12(x) > 0$, respectively, the class membership ξ WML(*x*) for the WML class may be found by

$$\xi WML = \begin{cases} \square ij(x), & x2 \le x \le x1 \\ 1 & x \ge x1 \end{cases} \qquad (15)$$

2. EXPERIMENTS

i) *Input Data Sets*:

A series of FLAIR images with WML are simulated based on fuzzy data base that contains a series of T1/T2/PD images with ground truth masks for GM, WM, CSF, and MS lesion classes. To generate FLAIR images from MR Imaging, the WM and GM classes are joined, resulting in three pure tissue classes: CSF, brain (GM and WM), and WML.

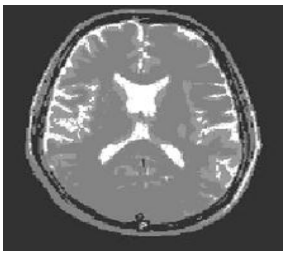

Fig.1 Input FLAIR MR Image

ii) *Analysis:*

The MR Images are fused using Multiple kernel fuzzy c means algorithm and Rough set theory. The data are classified using fuzzy membership classes. By using these values WML segmentation is carried out and then volumetric analysis is carried out. From these changes from both the hemisphere is calculated by taking the difference between two. That gives the chance of occurrence of stroke and carotid. The fuzzy classifier together with the rough set theory provides better results in improper pixel values. The feature extraction of imperfect pixels is carried out by rough set theory. By using energy function known as energy map that differentiate the white matter from the back ground. The energy map of the Fig.1 is obtained as shown below:

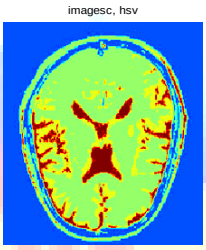

Fig.2 The energy mapped image

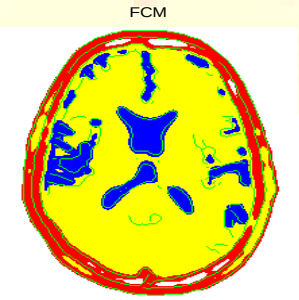

Fig.3 after applying FCM

iii) Results:

WML segmentation performs automatically, efficiently, and reliably. WML segmentation can further examine the relationship between WML, stroke, and carotid disease is the end goal. If can be applied on large dataset of patient, then this method is very efficient and further. However, the methods presented here give a clear sense of direction and show the potential of automated analysis for WML segmentation. As WML have been shown to be related to carotid disease, large differences in the hemispheric LLs could be an indication of advanced carotid disease. These are the subjects of future studies.

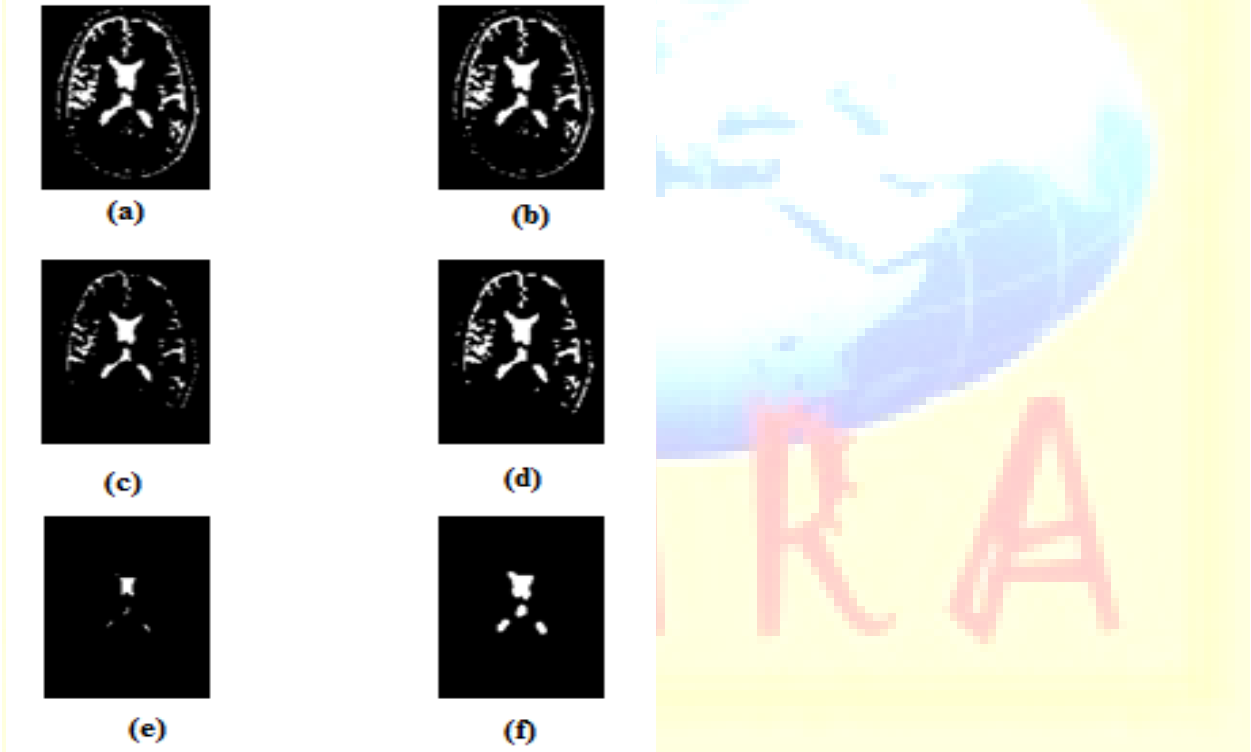

Fig.4. (a) PVA edge model output (b)-(d) different gray level estimations. (e) Image obtained after segmentation. (f) The final segmented output after smoothening.

3. CONCLUSION

A novel PVA quantification scheme is proposed that robustly segments WML in FLAIR MRI, as well as other tissue classes. Global edge-based approach including MKFCM and Rough

set Theory are used to measure the voxel intensity. The proposed algorithm can largely overcome the difficulties raised by noise, low contrast, and bias fields, and is capable of producing more accurate segmentation results than several state-of-the-art algorithms. Through Fuzzy classifier and the membership functions feature extraction of brain pixel values are effectively obtained. PVA is initially modelled with a localized edge strength measure since PVA resides in the boundaries between tissues. By the combined effect of rough set theory and fuzzy classifiers the exact volume is obtained after segmentation. LL studies can be used to measure the volume of the WML in the left and right hemispheres of the brain separately, that bring tremendous improvements in advance medical research on stroke and carotid disease. Further studies and researches are possible in this field.

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