Geostatistical and Fuzzy C-Mean Clustering For Extraction of White Matter

D.Sushma Deevi, G.S.Ajay K Reddy, Narendra Babu

Abstract - ***IMAGE technology allows medical researchers to observe details and to match morphological changes in the physical structure of the brain to changes in neurological and neuropsychiatric function such as cognitive performance over time. Following a vascular model, long-term changes in the vascular structure of the brain may appear as white matter lesions (WMLs) in cortical and sub cortical regions, which may directly or indirectly impact on brain functionality. White matter changes (lesions) are often seen in elderly people. Detection of white matter changes of the brain using magnetic resonance imaging (MRI) has increasingly been an active and challenging research area in computational neuroscience. There have rarely been any single image analysis methods that can effectively address the issue of automated quantification of neuroimages, which are subject to different interests of various medical hypotheses. Experimental results on MRI data have shown that the proposed image analysis methodology can be applied as a very useful computerized tool for the validation of our particular medical question, where white matter changes of the brain takes place in the people. This paper presents new clustering methods to separate the white matter from the brain image by using clustering techniques. First the MRI brain image is segmented, and the computational models of fuzzy c-means clustering, the effect geostatistics and the combined models of both the clustering techniques are obtained by fusion. There by, increasing the accuracy and time processing is decreased.***

Keywords—Fuzzy clustering, geostatistics, image egmentation, information combination, magnetic resonance imaging (MRI), white matter changes.

I. INTRODUCTION

Human brain white matter (WM) has been reported to experience degeneration as a consequence of normal aging and neurological disease. Although the clinical or functional consequences of WM degeneration are not well understood, clustering techniques and correlation studies have shown a close association between WM changes and motor function impairment. Because WM changes could be a predictive parameter for disease, WM degeneration has increasingly been of interest in brain research.

White matter changes (lesions) are often seen in elderly people. The significant effect of WMLs, however, is not fully under- stood and still to be investigated to validate possible associations between WML and other factors, such as cerebro-vascular risk, age, and cognitive impairment factors.

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D.Sushma Deevi, Department of Electronics and Communication Engineering, Lakireddy Balireddy Autonomous College of Engineerimg, Mylavaram-521230,A.p,India

G.S.Ajay K Reddy, Department of Electronics and Communication Engineering, Lakireddy Balireddy Autonomous College of Engineerimg, Mylavaram-521230,A.p,India

Narendra Babu' Department of Electronics and Communication Engineering, Lakireddy Balireddy Autonomous College of Engineerimg, Mylavaram-521230,A.p,India

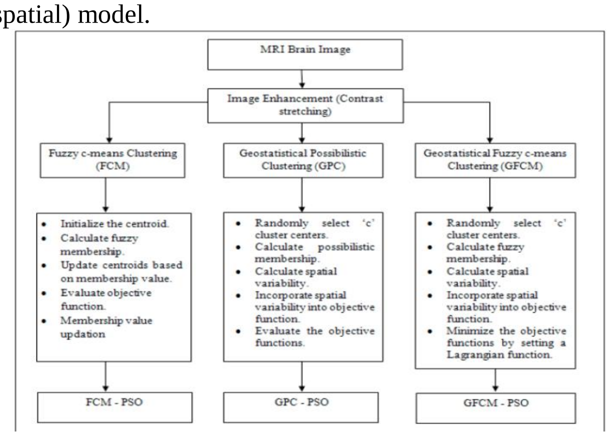
Accurate quantification of white matter changes may contribute to determining if it is possible to affect the evolution of white matter changes with pharmacological treatment, and if the rate of change would have any impact on cognitive performance or other tasks that require more complex cerebral processing.

The manual assessment on WML is still commonly used and is subject to different ratings, which make it no reproducible and difficult for a general agreement on medical downstream analysis. Furthermore, the development of MRI technology in recent years has resulted in much larger amounts of data that offer a great potential from a diagnostic point of view, but its sheer amount makes it difficult to analyze visually. These factors are propelling efforts in computer-assisted and automated quantitative MRI analysis.

The first step of automated quantification of WML involves image segmentation. Rare attention has been given to brain lesion segmentation in elderly individuals with relation to both depression and vascular disease, which is the focus of our study. Since MS lesions present different characteristics from lesions in elderly individuals, those methods are not directly applicable to our investigation because of the decreased contrast between white matter and gray matter in MRI in elderly.

One of the early developments for automatic segmentation of WMLs was the application of the *k*-nearest neighbors algorithm. This supervised learning method used the information from T1-weighted, inversion recovery (IR), proton density-weighted (PD), T2-weighted, and fluid attenuation IR (FLAIR) scans to estimate the probability of voxels being part of a WML. Binary segmentation results obtained from this method were dependent from the selected.In this paper, we present unsupervised models for automated detection of white matter changes.

The proposed segmentation models are derived by extending the objective functions of the fuzzy *c*-means (FCM) and the possibilistic clustering with a geostatistical (spatial) model.



II. TYPES OF CLUSTERING ALGORITHMS

In this we propose two of the most used clustering algorithms:

- Fuzzy C-means Clustering
- Geostatistical Fuzzy C-means Clustering

Fuzzy c-means has been a very important tool for image processing in clustering objects in an image. Fuzzy c-means (FCM) clustering is an unsupervised method derived from fuzzy logic that is suitable for solving multiclass and ambiguous clustering problems.

The fuzzy clustering of objects is described by a fuzzy matrix μ, with n rows and c columns in which n is the number of data objects and c is the number of clusters. μij, the element in the ith row and jth column in μ, indicates the degree of association or membership function of the ith object with the jth cluster. The characters of μ are as follows:

μij [0, 1], i=1, 2…., n, j=1, 2…., c (1)
where, **Σ**μ*ij =1, i=1, 2…., n* (2)
j=1
*0<***Σ** μ*ij<n, j=1, 2…., c* (3)

Main objective of fuzzy c-means algorithm is to minimize the objective function.

$$J(U,V)=\sum_{i=1}^{n}\sum_{j=1}^{c}(\mu_{ij})^m \, \| x_i - v_j \|^2 \quad (4)$$

where, m (m > 1) is a scalar termed the weighting exponent and controls the fuzziness of the resulting clusters and *'||xi – vj||'* is the Euclidean distance between ith data and jth cluster cener. The zj, centroid of the jth cluster.

$$Z_j=\frac{\sum_{i=1}^{n}(\mu_{ij})^{m}\,\mathbf{x_i}}{\sum_{i=1}^{n}(\mu_{ij})^{m}} \quad (5)$$

FCM Algorithm

S1 Randomly select *'c'* cluster centers.

S2 Compute the Euclidean distance, ||xi-*v*j||.

S3 Calculate the fuzzy membership according to the constraints of Eq. (1), (2) and (3).

S4 Calculate the fuzzy center according such that (5).

S5 Repeat steps 2) and 3) until the minimum 'J' value is incorporated, such that (4).

$$\mu_{i,j}=\frac{1}{\sum_{k=1}^{c}\left(\frac{\| x_i - c_j \|}{\| x_i - c_k \|}\right)^{\frac{2}{m-1}}}$$

Geostatistical Possibilistic Clustering (GPC)

To improve this weakness of FCM and to produce memberships that have a good explanation for the degree of belonging for the data, Possibilistic approach was proposed. It is a variation over fuzzy clustering where the membership to clusters can be seen as a degree of typicality membership matrix U, *uih* ∈ [0, 1]. Possibilistic clustering algorithms prove the fact that it can be applied for one cluster at a time.

$$J_{GP}(U,v)=\sum_{I=1}\sum_{J=1}(u_{ij})^m[d(x_i,v_j)]^2+\sum_{j=1}\frac{1}{(e_j)^2}\sum_{i=1}\left(1-u_{ij}\right)^m$$

where, $(e_j)^2$ is the kriging (geostatistical) variance of estimating vj using x_i, $i = 1…N-1$.

4.8.1. GPC Algorithm

S1 Randomly select *'c'* cluster centers according to (5).
S2 Calculate the possibilistic membership.
S3 Calculate the spatial variability.
S4 Incorporate spatial variability into objective functions as in (6).
S5 Minimize the objective functions (a small value of difference) then stop.

Geostatistical Fuzzy c-means Clustering (GFCM)

The fuzzy *C*-means objective function is generalized to include a spatial penalty on the membership functions. The fuzzy *C*-means algorithm (FCM) has been utilized in a wide variety of image processing applications such as medical imaging and remote sensing. Its advantages include a straightforward implementation, fairly robust behavior, applicability to multichannel data, and the ability to model uncertainty within the data. A major disadvantage of its use in imaging applications is that FCM does not incorporate information about spatial context, causing it to be sensitive to noise and other imaging artifacts. Therefore geostatistical fuzzy clustering is proposed.

The advantages of the new method are the following:

(1) It yields regions more homogeneous than those of other methods
(2) It removes noisy spots, and
(3) It is less sensitive to noise than other techniques

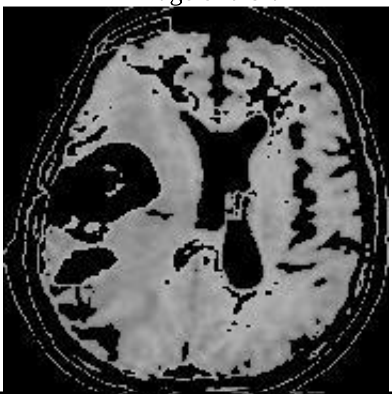
It is derived by extending the into the FCM objective function. Clustering is a two-pass process at each iteration. The first pass is the same as that in standard FCM to calculate the membership function in the spectral domain. In the second pass, the membership information of each pixel is mapped to the spatial domain, and the spatial function is computed from that. The FCM iteration proceeds with the new membership that is incorporated with the spatial function. The iteration is stopped when the maximum difference between two cluster centers at two successive iterations is less than a threshold. A distinctive observation of the incorporation of the geostatistical modeling into the fuzzy clustering is that it is able to accurately detect the WMLs as the regions of interest of an elderly population and provides the bidirectional association between depression and vascular disease. The main aim of is to minimize the objective function, where kriging variance is incorporated.

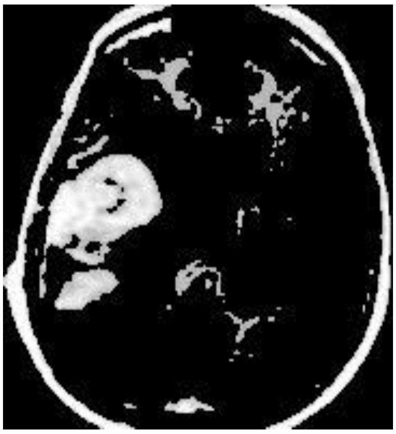
4.9.1. GFCM Algorithm

S1 Randomly select 'c' cluster centers.
S2 Calculate the fuzzy membership.
S3 Calculate the spatial variability.

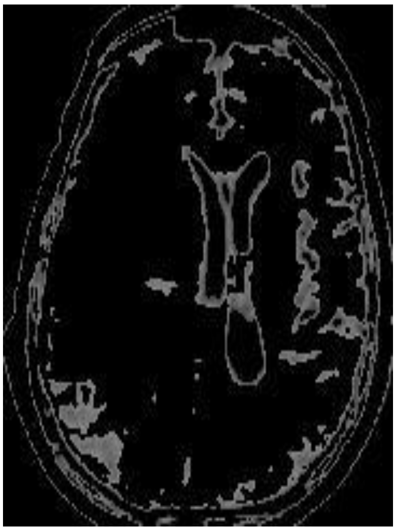
S4 Incorporate spatial variability into objective function such that (7).
S5 Minimize the objective functions by setting a Lagrangian function.

Mri image of a brain





These are the the different cluster images of the MRI image after applying the Fuzzy Clustering.



These are the the different cluster images of the MRI image after applying the Geostatistical Fuzzy Clustering.

III. CONCLUSION

This project is mainly focused on automated detection of White Matter Lesions of brain using fast and efficient clustering algorithms. The goal of our project is to cluster a medical image and simplify the representation of an image into a meaningful image so as to make it easier to analyze. As a first step, MRI brain image is pre-processed using Contrast Stretching technique which is one of the efficient image enhancement techniques. The pre-processed image is subjected to clustering. The clustering algorithms Fuzzy c-means Clustering (FCM) and Geostatistical Fuzzy Clustering Model (GFCM) have been successfully implemented.

By the fusion of techniques the similarities present in the both techniques has been tested and presented well, this has more accuracy regarding the information present in the brain image and also time required to process the both algorithms is also decreased. In application oriented, compared to other algorithms these algorithms are more robust and can be applied to real magnetic resonance images for noise reduction and other artifacts.

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AUTHORS PROFILE

G. S. Ajay Kumar Reddy, graduating in Department of Electronics and Communication Engineering at Lakireddy BaliReddy Autonomous Engineering College. Attended for about 6 International/National conferences/Seminars/Workshops.

D.Sushma Deevi, graduated in Department of Electronics and Communication Engineering at Lakireddy BaliReddy Autonomous Engineering College. Attended for about 2 International/National conferences/Seminars/Workshops.

Narendra Babu, presently working as head of the department for Electronics and Communication Engineering at Lakireddy BaliReddy Autonomous Engineering College. Attended more than 15 International/National conferences/Seminars/Workshops and leaded as project head in lbrce.