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Brain Tumor Segmentation of MRI Image using Gustaffson-Kessel (G-K) Fuzzy Clustering Algorithm

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Abstract:- Image segmentation plays a major role and an important role in the medical field due to its variety of applications especially in Brain tumor analysis. Brain tumor is an abnormal and uncontrolled growth of cells. It takes up space within the skull. It can compress, shift and harm healthy brain tissue and nerves. Also usually it obstruct with normal brain function. Tumors can be benign (non-cancerous) or malignant (cancerous), can happen in different parts of the brain. Brain tumor classification and identification from Magnetic Resonance (MR) data is an essential. But it takes time and manual task completed by medical specialists. Computerizing this task is a challenging because of the high variety in the look of tumor tissues among different patients and in many cases similarity with the normal tissues. In this work, brain tumor image has been segmented using proposed Gustafson-Kessel (G-K) fuzzy clustering algorithm. The performance of G-K segmentation method is compared with those of watershed and FCM algorithms.

Keywords *: Fuzzy, Clustering, Brain tumor, segmentation*

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I. INTRODUCTION

The human body contains a few sorts of cells with every cell having an exact function. The cells in the body develop and partition in a deliberate way which shapes new cells to keep the human body in great physical condition. While a couple of cells stop their ability to control their development, they develop in an improper manner which prompts additional cells to frame a mass of tissues called tumor. Brain tumors are a solid neoplasm inside the skull which usually grow in the brain or grow in other places such as in lymphatic tissue, in veins, in the cranial nerves and in the brain envelopes.

Image pre-processing is the initial step which is exceedingly required to guarantee the high precision of the ensuing strides. The experimental MR images ordinarily comprise various old rarities, for instance, intensity in homogeneities, extra cranial tissues, thus on which diminishes the general precision. Several authors are reported in the survey to reduce the cause of artifacts in the MR images. An examination on filtering concept with Gabor for noise analysis is done by Nicu et al.,[1]. But in the consequent years Chunyan et al.,[2] have implemented the color ray casting method to differentiate the region of interest from the background. Yong et al 2006 proposed the Diffusion filtering combined with simple non-adaptive intensity thresholding to enhance the region of interest. But this technique has the non-adaptive nature of the threshold value. The same concept has been discussed by Marianne et al.,[3] who have minimized the impacts between inter-slice intensity variation with the weighted LSE technique. The choice of weights for the LSE strategy is the significant detriment of this methodology. Bo et al.,[4] have proposed the noise elimination procedure by utilizing wavelets and curvelets.

Pathology identification is done by the image classification and after that the treatment is arranged taking into account the way of variation from the norm. After treatment, it is exceedingly fundamental to gauge the reaction of the patient to the healing. If there should be an occurrence of brain tumor variations from the norm, the measure of the tumor may diminish which demonstrates a constructive outcome and now and again it might increment which demonstrates a negative impact. Regardless, it is critical to play out a volumetric examination on MR brain tumor images. Image segmentation covers this goal by separating the strange part from the image which is valuable for breaking down the size and the state of the unusual locale. This strategy is additionally called “pixel based classification" since the individual pixels are bunched not at all like the grouping methods which sort the entire image. Very few researches have been carried out in the area of medical image segmentation. The image segmentation has been analyzed in two categories: (a) Non-Artificial Intelligence (NAI) techniques and (b) Artificial Intelligence (AI)techniques.

Abdelouahab et al.,[5] have reported that numerical morphology technique is applied for segmentation of MR brain image. The test results recommended the use of Skeleton by Influence ones detection (SKIZ) for brain image segmentation. Fusing et al.,[6] have built up a level set strategy- based tumor segmentation procedure. This strategy includes the technique for limit recognition with the seed point. Javad et al.,[7] have shown the utilization of Learning Vector Quantization (LVQ) for brain image segmentation. A similar examination is performed with the Back Propagation Neural Network (BPN) and the experimental results implemented by the LVQ. This report concludes that ANN-based classifiers are better than the other classifiers. Constantine et al [8] have executed Self Organizing Map construct segmentation procedure with respect to MR brain images. A few prior works taking into account fuzzy rationale hypothesis are likewise reported in the writing. Tai et al have executed a changed Fuzzy C-Means (FCM) calculation for mind image segmentation. This strategy appeared to give huge efficiency when contrasted and the routine FCM calculation. Absence of quantitative investigation on segmentation productivity is the disadvantage of this methodology. A more exact FCM calculation is proposed by Dzung et al.,[9].

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II. PRE-PROCESSING USING WEINER FILTER

This step improves the quality of data through the application of filters. In this work, the unwanted noise present in the brain MR image has been eliminated by using the Wiener filter. Normally, an IIR or FIR filters are used as Wiener Filter. Generally, the schematic of an IIR filter shows, it is in the structure of conditions or non-linear equations. However the FIR Wiener filter consists of conditions or linear equations and it seems to be a closed loop structure. In this research work, Wiener filter has been considered because it is easy to compute. The main disadvantage of FIR filter is, it requires a large number of coefficients to surmise an expected reaction over with IIR filter.

Wiener filters representation using a coefficient vector is shown in Figure 1. Input sign y(m) is applied to the Wiener filter and it produces the yield signal .

Where,

- Least Mean Square Error (LMSE) to estimate a desired or expected signal .The relation between input signal and output signal is expressed as

$$\hat{x}(m) = \sum_{k=0}^{P-1} [w_k * y(m-k)] \quad (1)$$

$$= w^T * y \quad (2)$$

where,

m - Discrete-time index

y^T is consider as filter input, and it is equal to [y(m), y(m–1), ..., y(m–P–1)]w^T = [w0, w1, ..., wP–1] -Wiener filter coefficient vector.

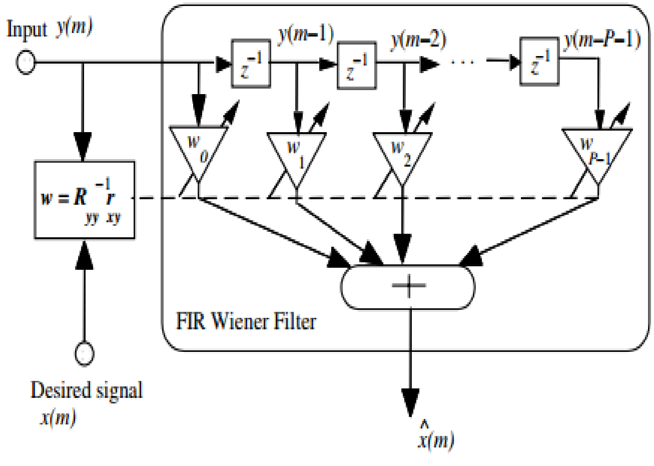

Figure 1: Schematic Representation of Wiener Filter

The Wiener filter is a very promising algorithm for removing noise from MR image. Three magnetic resonance imaging (MRI) images of human brain are considered in this work. The human brain MR image suffers from Rician noise. The size of the image is 256×256 and 16-bit signed integer. Figures 1 and 3 show the noisy MR image. Result from the experiment using the wiener filter is presented in Figures 2 and 4. The results shows that the Rician noise is removed significantly.

SAMPLE IMAGE 1

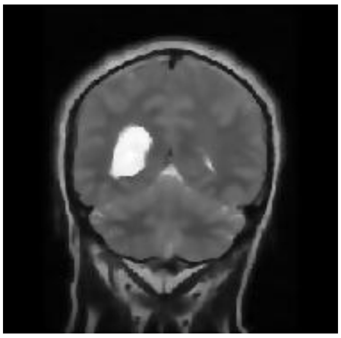

Figure 1 Original Image

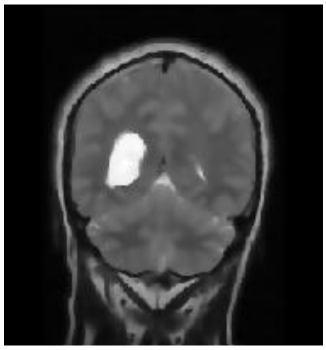

Figure 2 Wiener Filtered Image

SAMPLE IMAGE 2

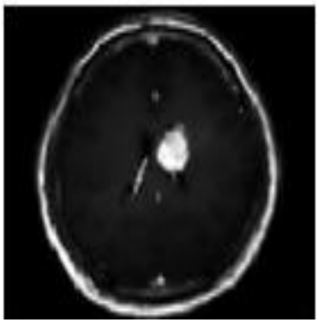

Figure 3 Original Image

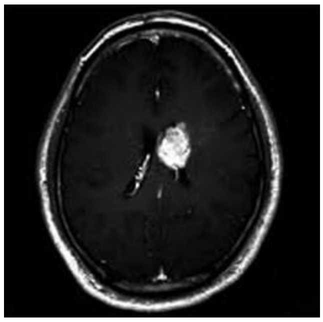

Figure 4 Wiener Filtered Image

PSNR values of sample image 1 and 2 are presented in Table 1.

$$PSNR = 10 \log_{10} \left[\frac{MAX_I^2}{MSE}\right] \quad (3)$$

Table 1.PSNR values of sample images

Sl. No.	IMAGE	PSNR
1.	Sample image 1	43.62
2.	Sample image 2	43.70

III. SEGMENTATION

Every image is a set of pixels and partitioning those pixels on the basis of similar characteristics they have is called segmentation. Dividing an image into sub partitions on the basis of some similar characteristics like color, intensity and texture is called image segmentation. The goal of segmentation is to change the representation of an image into something more meaningful and easier to analyze. Image segmentation is normally used to locate objects and boundaries that are lines, curves, etc. in images. In image segmentation image is divided into some regions and in those regions each pixel is similar with respect to some of the characteristics such as color, intensity or texture. Adjacent regions are different with respect to the characteristics.

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Segmentation can be done by detecting edges or points or line in the image. When one detects the points in an image then on the basis of similarities between any two points one can make them into separate regions. And in the case of the line detection technique, one uses to detect all the lines and the similarities in between those lines, then on the basis of the dissimilarities between the lines or curves in the image once can divide the image into two regions. In the case of edge detection we detect the edges in the image are detected and after finding the edges in the image one can easily divide the image, and here one can easily analyze what is inside the image and one can get a better segmented image.

A. Watershed segmentation method

A watershed definition for the continuous case can be based on distance functions. Depending on the distance function used one may arrive at different definitions. Assume that the image f is an element of the space C(D) of real twice continuously differentiable functions on a connected domain D with only isolated critical points (the class of Morse functions on D forms an example. Then the topographical distance between points p and q in D is defined by

$$T_f(p,q) = \inf_{\gamma} \int_{\gamma} \|\nabla f(\gamma(s))\| \, \mathrm{d}s \, ,$$

where the infimum is over all paths (smooth curves) γ inside D with γ(0) = p, γ(1) = q. The topographical distance between a point p ∈ D and a set A ⊆ D is defined as Tf (p, A) = mina∈A Tf (p, a). The path with shortest Tf -distance between p and q is a path of steepest slope. This motivates the following rigorous definition of the watershed transform. (Watershed transform) Let f ∈ C(D) have minima {mk}k∈I , for some index set I. The catchment basin CB(mi) of a minimum mi is defined as the set of points x ∈ D which are topographically closer to mi than to any other regional minimum mj :CB(mi) = {x ∈ D | ∀j ∈ I\{i} : f(mi) + Tf (x, mi) < f(mj) + Tf (x, mj)}

The watershed of f is the set of points which do not belong to any catchment basin:

$$Wshed(f) = D \cap \left(\bigcup_{i \in I} CB(m_i) \right)^c$$

Let W be some label, W ∈ I. The watershed transform of f is a mapping λ : D → I ∪ {W}, such that λ(p) = i if p ∈ CB(mi), and λ(p) = W if p ∈ Wshed(f).

B. FUZZY CLUSTERING

Fuzzy clustering can be used as a tool to obtain a partitioning of data where the transitions between the subsets are gradual rather than abrupt. This section gives an introduction to the basic concepts of fuzzy clustering and simultaneously serves as a reference to clustering algorithms that can be used to construct T-S fuzzy models from data.

Cluster Analysis

The objective of cluster analysis is the classification of objects according to similarities among them and the organizing of data into groups. Clustering techniques are among the unsupervised (learning) methods, since they do not use prior class identifiers. Most clustering algorithms also do not rely on assumptions common to conventional statistical methods, such as the underlying statistical distribution of data and therefore they are useful in situations where little prior knowledge exists. The potential of clustering algorithms to reveal the underlying structures in data can be exploited, not only for classification and pattern recognition, but also for the reduction of complexity in modeling and optimization.

Prior to clustering, the regression structure of the model is selected, in order to properly represent the system dynamics. Problems where little prior knowledge is available are usually represented in an input-output form. After the structure is determined, clustering in the product space of the regressors and of the regressand can be applied to partition the data. Since each cluster serves as a local linear model of the system

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Fuzzy Partition

From the available input/output data pairs, the regression matrix X and the output vector y are constructed as given by

$$X^T = [x_1, \ldots x_N] \text{ and } y^T = [y_1, \ldots y_N]. \tag{4}$$

where N>>n is the number of samples used for identification. The antecedent fuzzy sets A_i in are determined by means of fuzzy clustering in the product space of the systems input and outputs. Hence, the data set $Z = R^{(n+1) \times N}$ to be clustered is represented as a $(n+1) \times N$ data matrix composed from X and y. Each column of $Z_{k,}$ k = 1,2,…,N contains an input/output data pair as given by

$$Z_k = [X_k^T, y_k^T] \tag{5}$$

$$U = \begin{bmatrix} \mu_{11} & \mu_{12} & \mu_{1c} \\ \mu_{21} & \mu_{22} & \mu_{2c} \\ \vdots & \vdots & \vdots \\ \mu_{N1} & \mu_{N2} & \mu_{Nc} \end{bmatrix} \tag{6}$$

Given Z and an estimated number of clusters 'c', fuzzy clustering partitions *Z* into 'c' fuzzy clusters. Each cluster forms one fuzzy rule. A fuzzy partition can be represented as an 'N × c' matrix U, whose elements $\varphi_i(x) \in [0, 1]$ represents the membership degree of Z_k in clusters 'i'. Hence, the i^{th} column of U contains the values of the membership function in the fuzzy partition, which is taken to be a point wise representation of the antecedent fuzzy set A_i of the i^{th} rule . The sum of each column of U is constrained to one, but the distribution of membership among the 'c' fuzzy subsets is not considered. Also, there can be no empty clusters and no cluster may contain all the objects. This means that the membership degrees in the partition matrix U are normalized, and for the given identification data, the membership values $\varphi_i(x)$ correspond to the normalized degree of fulfillment of the rule antecedents. In this work, membership functions for antecedent are extracted using FCM and Gustafson-Kessel (G-K) clustering algorithms.

Fuzzy C-Means algorithm

Most analytical fuzzy clustering algorithms are based on optimization of the basic C-Means objective function, or some modification of it. The advantage of FCM algorithm is simplicity and easy implementation. Given the data set Z, choose the number of clusters as 1<c<N, the weighting exponent m > 1. The termination tolerance $\varepsilon > 0$ and the norm-inducing matrix A. Initialize the partition matrix randomly such that $U^{(0)} \in M_{fc}$. When the termination tolerance is achieved, the values of membership functions are obtained as given in eqn. (9). The following steps are repeated using MATLAB software for j =1,2,…,.

Step (1): Compute the cluster prototypes (means):

$$V_i^{(j)} = \frac{\sum_{k=1}^{N} (\mu_{ik}^{(j-1)})^m Z_k}{\sum_{k=1}^{N} (\mu_{ik}^{(j-1)})^m}, 1 \le i \le c \quad (7)$$

Step (2): Compute the distances:

$$D_{ikA}^2 = (Z_k - V_i^{(j)})^T A (Z_k - V_i^{(j)}), \quad (8)$$
$$1 \le i \le c,\ 1 \le k \le N$$

Step (3): Update the partition matrix:

If $D_{ikA} > 0$ for $1 \le i \le c, 1 \le k \le N$,

$$\mu_{ik}^{(j)} = \frac{1}{\sum_{n=1}^{c} (D_{ikA}/D_{nkA})^{2/(m-l)}}$$

Otherwise

$$\mu_{ik}^{(j)} = 0 \text{ if } D_{ikA} > 0, \text{ and } \mu_{ik}^{(j)} \in [0,1] \quad (9)$$
$$\text{with } \sum_{i=1}^{c} \mu_{ik}^{(j)} = 1$$

Until $\| U^{(j)} - U^{(j-1)} \| < \varepsilon$.

C. GUSTAFSON-KESSEL (G-K) CLUSTERING ALGORITHM

Gustafson and Kessel extended the standard FCM algorithm by employing an adaptive distance norm, in order to detect clusters of different geometrical shapes in one data set. Each cluster has its own norm-inducing matrix A_i. The matrices A_i are used as optimization variables in the C-Means functional, thus allowing each cluster to adapt the distance norm to the local topological structure of the data. Given the data set Z, choose the number of clusters as 1<c<N, the weighting exponent m > 1 and the termination tolerance $\varepsilon > 0$. Initialize the partition matrix randomly such that $U^{(0)} \in M_{fc}$. The following steps are repeated using MATLAB software for j=1,2… The G-K algorithm is same as that of FCM, only the computation of distance measure is calculated using co-variance matrices as follows:

Step (1): Compute the cluster prototypes (means):

$$V_i^{(j)} = \frac{\sum_{k=1}^{N} (\mu_{ik}^{(j-1)})^m Z_k}{\sum_{k=1}^{N} (\mu_{ik}^{(j-1)})^m}, 1 \le i \le c \quad (10)$$

Step (2): Compute the cluster covariance matrices:

$$F_i = \frac{\sum_{k=1}^{N} (\mu_{ik}^{(j-1)})^m (Z_k - V_i^{(j)})(Z_k - V_i^{(j)})^T}{\sum_{k=1}^{N} (\mu_{ik}^{(j-1)})^m}, \quad (11)$$

where $1 \le i \le c$.

Step (3): Compute the distances:

$$D_{ikA}^2 = (Z_k - V_i^{(j)})^T * \left[(\rho_i \det(F_i)^{1/n} F_i^{-1} \right] * (Z_k - V_i^{(j)}),$$
$$1 \le i \le c,\ 1 \le k \le N \quad (12)$$

Step (4): Update the partition matrix:

IF $D_{ikA} > 0$ for $1 \le i \le c, 1 \le k \le N$,

$$\mu_{ik}^{(j)} = \frac{1}{\sum_{n=1}^{c} (D_{ikA}/D_{nkA})^{2/(m-l)}}$$

Otherwise

$$\mu_{ik}^{(j)} = 0 \text{ if } D_{ikA} > 0, \text{ and } \mu_{ik}^{(j)} \in [0,1] \quad (13)$$
$$\text{with } \sum_{i=1}^{c} \mu_{ik}^{(j)} = 1$$

Until $\| U^{(j)} - U^{(j-1)} \| < \varepsilon$.

Figure 6 and 7 shows the segmented brain tumor image using watershed, FCM and G-K algorithms. The performance of the segmentation technique is analyzed based on computation time and Dice Similarity Coefficient (DSC) values and it is summarized in Table 2. From the values it is observed that the G-K gives satisfactory result than the other techniques. The main validation metric of brain MR image is DSC. The DSC measures the overlap between two segmentations, A and B target regions, and is defined as DSC(A,B)= 2(A∩B)/(A+B).

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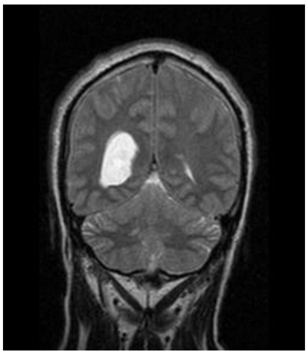

Fig. 5 (a) Filtered image

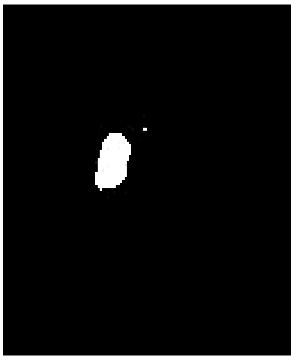

Fig. 5 (b) Segmented output (G-K)

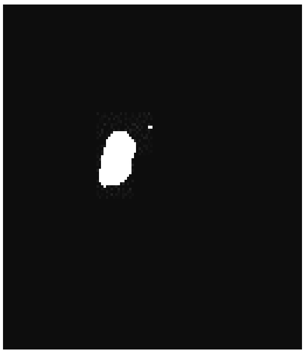

Fig.5(c)Segmentedoutput(FCM)

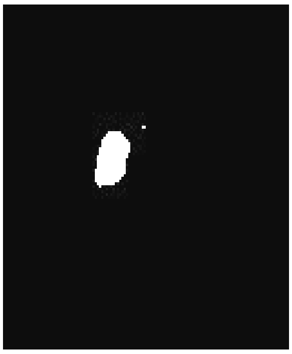

Fig.5(d)Segmented output (Watershed)

SAMPLE IMAGE 2

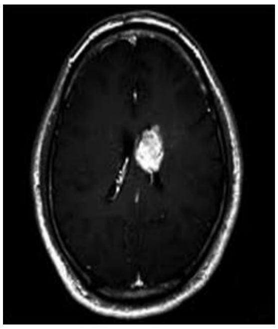

Fig. 6 (a) Filtered image

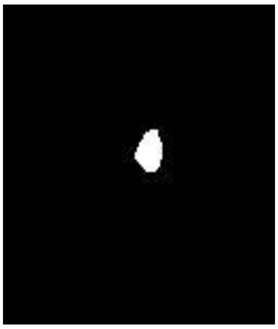

Fig. 6 (b) Segmented output (G-K)

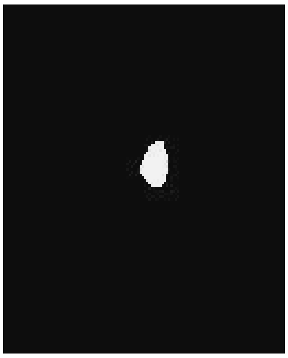

Fig. 6 (c) Segmented output (FCM)

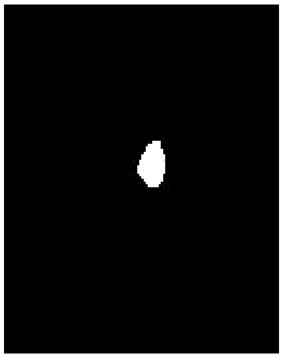

Fig.6(d) Segmented output (Watershed)

Table 2. Performance Analysis

Algorithm	Computation Time (Seconds)	DSC Values
Watershed	0.35	0.92
FCM	0.30	0.90
G-K	**0.27**	**0.88**

IV CONCLUTION

In this work, Pre- processing of brain MR image has been carried out using Wiener filter. The segmentation has been completed by utilizing Watershed, FCM and G-K methods. The performance of G-K has been compared with those of FCM and Watershed algorithms. From the result is clear that G-K algorithm produces better result compared with those of watershed and FCM algorithms in terms of computation time and DSC values.

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