Assimilated Strong Fuzzy C-means in MR Images for Glioblastoma Multiforme

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Abstract

Background/Objectives: In this paper we segment breast and brain Magnetic Resonance Images. Methods/Statistical Analysis: This automated process implemented by a robust Fuzzy C-Means (FCM). This FCM needs novel objective function. This is obtained by performing replacement. The source is original Euclidean distance. Findings: The target is properties of kernel function on feature space. This transformation uses Tsallis entropy. The effective objective functions are minimized. It results in membership partition matrices and successive prototypes with equation. The initial cluster reduces both the running time and computational complexity. The synthetic image with benchmark dataset used to perform initial experimental work. Then it is applied to real breast and brain magnetic resonance image on different region. Conclusion/Improvements: The silhouette method shows better segmentation than existing method.

Keywords: Center Knowledge, Clustering, Fuzzy C-Means, Image Segmentation, Kernal Function, MR Imaging

1. Introduction

Glioblastoma multiforme (GBM) is the brain tumor which is malignant in nature and most common in humans, as shown in Figure 1. It accounts for more than 50% of all functional tissue brain tumor cases and more than 20% of all intracranial tumors. In an endeavor to stipulate beyond astuteness imminent this organ, the number of explorations of the brain has been fostering during the preceding century. Contemporary modus operandi have endorsed cumulative the acquaintance in the borough of the brain structures and its manoeuvring11. For unknown reasons, GBM occurs more commonly in males4. The glioblastoma tumors tends to be sporadic and without any genetic predisposition. Glioblastoma and smoking have no link between them5. Consumption of cured meat6 or electromagnetic fields7-10. Alcohol consumption may be a possible risk factor11. Glioblastoma has been associated with the viruses SV4012 cytomegalovirus13. There also appears to be a minute link between glioblastoma and ionizing radiation14. Some believe that there exists a link between glioblastoma and polyvinyl chloride (which is commonly used in construction)15. A 2006 analysis links brain cancer have effect in the work-place16. There is an association of malaria and brain tumor incidence, suggesting that the anopheles mosquito, that could cause glioblastoma.

The normal adult human brain innately ponders between 1 and 1.5 kg and has an average volume of 1,600 cm3–12. Even though clustering procedures fabricate a panel of data into clusters, with similar entities grouped in a cluster and dissimilar entities in different clusters and are one of the most primary modes of understanding and learning. In clustering process, the dissimilarity between any two elements of the dataset can be computed using distance measures. Cluster analysis has been extensively used in several applications, including segmentation of medical images, market research, pattern recognition, data analysis and image processing (Dubes and Jain, 1980; Yong, et al. 2004). Clustering approaches have been divided into two schemes, such as the hard clustering scheme and the fuzzy clustering scheme. The hard clustering method

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experts. But manual segmentation is a complicated and a time consuming task, which makes an automated breast and brain tumor segmentation (Chen, et al. 2006; Xing, et al. 2007) method desirable. The automated segmentation (Sikka, et al. 2009; Ketsetzis and Gand Brady, 2004; Wu, et al. 2006) is an interesting field in medical image analysis. Artificial intelligence techniques based automated segmentation methods were proposed in (Clark, et al. 1998; Fletcher-Heath, et al. 2001). Using a multi-layer Markov random field framework, Gering, et al. (2002) developed a method that identifies deviations from normal brains. In recent times, Fuzzy C-Means (FCM) of unsupervised clustering techniques used in an automated segmentation of medical images on established outstanding results in a strong way. Fuzzy C-Means clustering algorithm (Bezdek, et al. 1993; Lyer, et al. 2002; Yang, et al. 2002) is effectively applied in various fields such as astronomy, geology, medical imaging, target recognition and image segmentation (Chen, et al. 2006). Even though Fuzzy C-Means algorithm having significant profit in segmentation of medical images, it has some disadvantages such as the membership of data element has not strong enough or extensively high for a particular cluster, it means that the expression of computing membership is not very effective to cluster the data elements. In order to overcome the drawback of conventional FCM algorithm, some modified Fuzzy C-Means (Hathaway and Bezdek, 2006; Pal and Bezdek, 2002; Hathaway and Hu, 2009) have been proposed to improve the performance of standard FCM algorithm and to decline its computational complexity. Though various modified FCM algorithms have been introduced by researchers, still the data elements that are far from all cluster centers in the result of fuzzy partitioning process (Ichihashi and Honda, 2005).

Adaptive Network-Based Fuzzy Inference System (ANFIS), k-Nearest Neighbors (k-NN) and Fuzzy C-Means (FCM) in brain tumor segmentation. T. Logeswari presents a brief comparison with other classifiers, main advantages and drawbacks of proposed classifier are analyzed. Rami J. Oweis presents the pixel classification of medical image using neuro fuzzy approach, which is based on spatial properties of the image features. N. Benamrane has proposed an approach which combines Neural Networks, Fuzzy Logic and Genetic Algorithms as a hybrid system. For extracting image it uses region growing method. Ian Middleton uses a neural network (a Multi Layer Perceptron, MLP) and active contour model (‘snake’) to segment tumor in Magnetic Resonance (MR) images.

Figure 1. Analytical activities of the GBM in brain.
Ramiro Castellanos\textsuperscript{15} presents an image segmentation technique which uses Adaptive Fuzzy Leader Clustering (AFLC) algorithm. Because pixel-based methods based on K-means clustering are simple and the computational complexity is relatively low compared with other region-based or edge-based methods, the application is more practicable. Furthermore, K-means clustering is suitable for biomedical image segmentation as the number of clusters is usually known for images of particular regions of the human anatomy. Many researchers have proposed related research into K-means clustering segmentation\textsuperscript{1,5}. The improvements achieved by\textsuperscript{1,5} have been remarkable, but more computational complexity and extra software functionality are required. In this paper, we carefully select the appropriate features from brain images as the clustering features to achieve good segmentation results while maintaining the low computation aspect of the segmentation algorithm. Because the color space transformation function in our proposed method is a fundamental operation for most image processing systems, the color space translation does not cause extra overhead in the proposed scheme. Therefore, by using color-based segmentation with K-means clustering To Magnetic Resonance (MR) brain tumors, the proposed image tracking method maintains efficiency. The experimental results also confirm that the proposed method helps pathologists distinguish exact lesion sizes and regions. Madhulika Bhatia\textsuperscript{27} proposed an algorithm to Blotch Grey Matter from Tumored and Non Tumored Brain MRI Images.

2. Methodology

2.1 Existing Method

Generally Fuzzy C-Means uses a Euclidean distance measure to assign fuzzy memberships to data element for clustering the data, it provides good clustering result for only noise free dataset. To overcome this drawback, many other algorithms have been proposed to obtain capable results in segmentation of medical images by replacing the Euclidean norm with kernel distance measures named as kernel based FCM (KFCM). The problem of KFCM for image segmentation is it does not take into consideration any spatial dependence of the data elements, which makes it very sensitive to noise and other imaging artifacts. Ahmed, et al.\textsuperscript{2} (2002) proposed a Fuzzy C-Means algorithm with spatial constraints (FCM S), which is robust to noise, but the disadvantage of this algorithm is that it is very time consuming for computing the neighborhood term in every step. Zhang and Chen (2003) developed a variant of FCM S, FCM S1 and FCM S2, which simplified the neighborhood term of FCM S by mean-filtered image and median-filtered image to reduce the computation. The addition of spatial penalty term to the basic KFCM was proposed by Zhang and Chen (2004) for medical image segmentation. The limitations of KFCM S algorithm is that it calculates the neighborhood term in successive iteration of the clustering process, which takes more time to converge the algorithm and also the updated centers lead the clustering result might be inappropriate with datasets which are affected by heavy noise.

2.2 Disadvantages

This paper comprehend the highlighted drawbacks and it tries to eradicate the drawbacks by introducing novel robust objective function of Fuzzy C-Means with incorporating the concept of normed induced kernel function and Tsallis entropy for segmenting medical images effectively. Further in order to circumvent the unstable clustering outcome by the random initialization of cluster centers, this paper introduces a new cluster center initialization algorithm for initializing cluster center for our proposed method. The experimental results show that the proposed methods are powerful tool in clustering synthetic images, benchmark dataset and real images than the listed existed methods.

2.3 Proposed Method

This subsection proposes Robust Fuzzy C-Means based Kernel function (RFCMK) by incorporating normed kernel function and center initialization algorithm. The proposed robust normed induced distance Fuzzy C-Means transforms the original pattern space into a higher dimensional feature space using nonlinear transformations. Therefore, the new novel Fuzzy C-Means leads to cluster complex noised dataset of image into more appropriate groups. This section uses the following standard objective function of Fuzzy C-Means to construct the effective objective function for RFCMK.

\[ J(U,V) = \sum_{i=1}^{n} \sum_{k=1}^{c} u_{ik}^m ||x_i - v_k||^2 \]

- U is a fuzzy partition matrix of X.
- \( v = (v_1, v_2, \ldots, v_c) \in \mathbb{R}^{qc} \) with \( v_k = (v_{1k}, v_{2k}, \ldots, v_{qk}) \)
- \( T \in \mathbb{R}^q \) is the cluster center of kth cluster, \( 1 \leq k \leq c \).
• $x_i - v_k$ is Euclidean distance between the object $x_i$ and center $v_k$.
• $m$ is the weighting exponent (also called the degree of fuzzifier) $m \in (1, \infty)$.

The above is the objective function of proposed RFCMK and the proposed partition matrix in an objective function satisfies the following constraints:
\[ 0 \leq u_{ik} \leq 1, \text{ for } 1 \leq i \leq n, 1 \leq k \leq c, \]

### 2.4 Algorithm

Step 1: Get data from image.
Step 2: Select the number of clusters and initialize the prototypes using Center initialization algorithm.
Step 3: Initialize the partition matrix using the above equation.
Step 4: Update the cluster centers using FCM.
Step 5: Repeat steps (3 and 4) until the following termination criterion is satisfied.

### 3. Medical Data Scrutiny

List of Modules:
- Robust Fuzzy C-Means based kernel function.
- Obtaining memberships partitioned.
- Obtaining successive centers or prototypes.
- Tsallis entropy based Fuzzy C-Means.
- Obtaining successive centers or prototypes.

#### 3.1 Robust Fuzzy C-Means based Kernel Function

This subsection proposes Robust Fuzzy C-Means based Kernel function (RFCMK) by incorporating normed kernel function and center initialization algorithm. The proposed robust normed induced distance Fuzzy C-Means transforms the original pattern space into a higher dimensional feature space using nonlinear transformations. Therefore, the new novel Fuzzy C-Means leads to cluster complex noised dataset of image into more appropriate groups.

#### 3.2 Obtaining Memberships Partitioned

We minimize the objective function which is given with respect to $u_{ik}$, subject to the constraints:
\[ u_{ik} = \left( \frac{\gamma^2}{2m(\beta - K(x_i, v_k))} \right)^{\frac{1}{m-1}} \]

In general the expression is modified to:
\[ u_{ik} = \left( \frac{1}{\beta - K(x_i, v_k)} \right)^{\frac{1}{m-1}} \]
\[ \sum_{j=1}^{c} \left( \frac{1}{\beta - K(x_i, v_j)} \right)^{\frac{1}{m-1}} \]

The above general equation is used to obtain membership grades for objects in dataset to find appropriate groups.

#### 3.3 Obtaining Successive Centers or Prototypes

By minimizing the objective function the following algorithm is expressed in here;

Step 1: Get data from image.
Step 2: Select the number of clusters and initialize the prototypes using center initialization algorithm.
Step 3: Initialize the partition matrix using the above equation.
Step 4: Update the cluster centers using FCM.
Step 5: Repeat steps (3 and 4) until the following termination criterion is satisfied:
\[ \left\| V^{\text{present}} - V^{\text{previous}} \right\| < \varepsilon \]

It mentions that the vector of cluster prototypes at present iteration and previous iterations.

#### 3.4 Tsallis Entropy based Fuzzy C-Means

In order to distinguish the similar intensity object of different clusters, this subsection exhibits Tsallis entropy with new kernel induced objective function of Fuzzy C-Means called as Tsallis Entropy based Fuzzy C-Means (TEFCM). The objective function of TEFCM is formulated as;
\[ J(U, V) = 2 \sum_{i=1}^{n} \sum_{k=1}^{c} u_{ik} \left( \beta - K(x_i, v_k) \right) + \frac{\alpha}{\gamma - 1} \left( \sum_{i=1}^{n} \sum_{k=1}^{c} u_{ik}^{-\frac{1}{\gamma-1}} \right) \]

where $\mu > 1$ defined by user and the larger value leads the membership degree of the data elements as uniform, $i$ represents a linear weighted sum of each data.
3.5 Obtaining Successive Centers or Prototypes

The appropriate cluster centers are used to capture the appropriate structure of data in each cluster. In order to attain the effective updating equation for cluster center, the objective function is minimized with respect to \( v_k \).

In general the equation is expressed below:

\[
v_k = \frac{\sum_{i=1}^{n} u_{ik}^g x_i}{\sum_{i=1}^{n} u_{ik}^g}, \quad k = 1, 2, \ldots,
\]

This effectual cluster center updating equation used to find well final clusters.

Step 1: Get data from image.
Step 2: Select the number of clusters and initialize the prototypes using center initialization algorithm.
Step 3: Initialize the partition matrix using (24,25).
Step 4: Update the cluster centers using (26,28,29).
Step 5: Repeat steps (3 and 4) until the following termination criterion is satisfied.

4. Experiment Result

The programming language used with MATLAB is usually named as M-script. When you develop programs using MATLAB, you can output the results, including graphics files, HTML pages, PDF files and Word documents. You can also extend the use of MATLAB with applications such as Excel or LabView to make extended uses of it. Since it uses JAVA program as a part, you can modify it in the background using Java.

The feasibility of the project is analyzed in this phase and business proposal is put forth with a very general plan for the project and some cost estimates. During system analysis the feasibility study of the proposed system is to be carried out. These data sets have been acquired on 1.5T Philips achieva apparatus and 1.5T G.E apparatus using an axial T1-weighted sequence with contrast agent. The proposed method was verified on MR brain image data sets of five patients named as patient 1 to patient 5 where one slice was selected from the data set of each patient to analyze the performance of the proposed method. This is to ensure that the proposed system is not a burden to the company. For feasibility analysis, some understanding of the major requirements for the system is essential. Input Images in MRI, as shown in Figure 3. Initial iteration based on Strong FCM, as shown in Figure 4. Iteration Image Snapped at the Middle Stage, as shown in Figure 5. Iteration Performed to Identify Tumor regions, as shown in Figure 6. Internal Iteration, Boundary Analysis, Filtered Region, Segmented MR image, as shown in Figure 7 (a,b,c,d). Histogram Analysis of the Processed Image, as shown in Figure 8.

5. Screenshots

5.1 Input Image
5.2 Processing Image

Initial Iteration

Figure 4. Initial Iteration based on Strong FCM.

Fifth Iteration

Figure 5. Iteration image snapped at the middle stage.

Final Iteration

Figure 6. Iteration performed to identify tumor regions.

In computational mathematics, an iterative method is a mathematical procedure that generates a sequence of improving approximate solutions for a class of problems. A specific implementation of an iterative method, including the termination criteria, is an algorithm of the iterative method. An iterative method is called convergent if the corresponding sequence converges for given initial approximations. A mathematically rigorous convergence analysis of an iterative method is usually performed; however, heuristic-based iterative methods are also common. Stationary iterative methods solve a linear system with an operator approximating the original one; and based on a measurement of the error in the result (the residual), form a “correction equation” for which this process is repeated. While these methods are simple to derive, implement and analyze, convergence is only guaranteed for a limited class of matrices. Examples of stationary iterative methods are the Jacobi method, Gauss–Seidel method and the Successive over-relaxation method. Linear stationary iterative methods are also called relaxation methods.
5.3 Segmented Image based on FCM

![Segmented Image based on FCM](image)

**Figure 7.** (a) Internal Iteration (b) Boundary Analysis (c) Filtered Region (d) Segmented MR image.

6. Conclusion

6.1 Conclusion

This paper proposed robust Fuzzy C-Means algorithms for segmentation of brain and breast medical images based on standard FCM and properties of kernel functions. To evaluate the effectiveness of proposed methods, we compared the results of RFCMK and TEFCM with the results of standard FCM, KFCM and spatial constrained KFCM. This paper implemented the proposed RFCMK and TEFCM with synthetic image and Iris dataset, before to implement it to real breast and brain MRIs. Now we introduce KFCM and KFCM S to synthetic image to test its effect on clustering performance. It shows the results of KFCM and KFCM S on synthetic image. It is observed from Figure 7(a and b) that almost the same results of as standard FCM given. Both the algorithms KFCM and KFCM S have obtained the results with 11 iterations.

6.2 Future Works

It is observed from our comparison that the proposed RFCMK and TEFCM with center initialization algorithm performed well than FCM, KFCM, Spatial constrained KFCM. Also the proposed algorithms produce high segmentation accuracy than FCM, KFCM and spatial constrained KFCM. The results reported in this paper show that the proposed RFCMK and TEFCM is an effective approach to construct a robust image segmentation algorithm. And this work hopes that the proposed methods can also be used to improve the performance of other FCM-like algorithms based on Euclidean distance functions.

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