




## Review and Comparison of Three Clustering Methods: FCM, HCM, and C-Means for Brain Tumor Image Detection

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ARTICLE INFO	ABSTRACT
<p>Article History:            Received 5 June 2018            Received in revised form 13 August 2018            Accepted 27 September 2018            Available online 29 September 2018</p>	<p>The application of computers in medical fields has significantly increased compared to the past, revolutionizing how healthcare professionals process, analyze, and interpret clinical data. Today, we observe extensive use of advanced computational techniques, including machine learning and data mining, in analyzing complex medical datasets and extracting meaningful insights. One of the most critical and impactful applications of computer methods in the medical sciences is the segmentation and analysis of medical images, which plays a vital role in supporting diagnosis, treatment planning, and disease monitoring. Among various medical imaging challenges, brain tumor image segmentation has garnered considerable research attention in recent years, as accurate delineation of tumor boundaries is essential for effective clinical decision-making and improving patient outcomes. Numerous segmentation techniques have been proposed, among which clustering algorithm-based solutions stand out due to their flexibility and effectiveness in handling medical image data. In particular, fuzzy clustering methods have emerged as powerful tools because they account for the inherent ambiguity and uncertainty present in medical images. This paper focuses on evaluating and comparing three prominent clustering algorithms Hard C-Means (HCM), Fuzzy C-Means (FCM), and traditional C-Means with the aim of examining their relative strengths, limitations, and suitability for the specific task of brain tumor image segmentation. The results offer valuable insights into their comparative performance and practical applications.</p>
<p>Keywords:            Image Segmentation, Brain Tumor Image, Clustering Algorithm</p>	

### 1. INTRODUCTION

Image segmentation is an essential preprocessing step in image processing, dividing an image into regions with similar attributes. The current significant issue is finding an automatic, fast, and straightforward method capable of segmenting a digital image [1,2]. Segmentation approaches, due to their simplicity and effectiveness, were among the first techniques used for clustering natural images. Monochrome image segmentation approaches are based on the discontinuity and/or similarity of gray level values in a region. If the approach is based on discontinuities, an image is segmented using the identification of points, lines, and edges according to sudden changes in gray levels.

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Similarity and homogeneity-based approaches include region growing, clustering, thresholding, and region splitting and merging. The goal of these approaches is to group pixels and transform them into specific regions [2].

Multilevel histogram is one of the techniques widely used in monochrome image segmentation. It is assumed that images consist of regions with ranges of different gray levels, and a histogram of an image can be assigned several peaks, each corresponding to a region, with a threshold value between the valleys of two adjacent peaks. However, for color images, due to the multi-feature property, the situation differs from monochrome images. Multilevel histogram thresholding in color space divides the color space using the histogram threshold of each part. There are constraints when dividing multidimensional spaces because thresholding is a technique for grayscale images. For example, the shape of clusters is rectangular. Since color information is displayed using G, R, and B colors or their linear/nonlinear transformations, displaying the histogram of a color image in a three-dimensional array and selecting the threshold in this histogram is a non-trivial task, and discovering clusters of points within the space involves heavy computation [3,6].

Specifying the threshold value(s) in image segmentation is arguably the most crucial part of this task. Many methods have been proposed in this area, yielding noteworthy results. However, considering that image segmentation is a heavy optimization problem, a comprehensive and complete algorithm or method for solving this problem has not been found yet. Many articles have been presented in the past on the use of swarm intelligence algorithms, such as genetic algorithms, for finding threshold values in digital image segmentation. However, despite the genetic algorithm's strong capability in global search, it performs weakly in local search. This weakness has prevented the genetic algorithm from yielding suitable results in this area on its own [4]. The rest of the paper is organized as follows: Section 2 reviews clustering methods, Section 3 presents the clustering algorithms FCM, HCM, and C-Means, Section 4 discusses the advantages and disadvantages of each mentioned algorithm, and the last section concludes the paper and presents the results.

## **2. REVIEW OF CLUSTERING METHODS**

In this chapter, we aim to examine methods for segmenting color and grayscale images. One of the most practical clustering methods in this field of study is clustering algorithms. We will review the most important segmentation methods based on the use of multilevel histogram determination and pixel clustering.

Typically, the first step in image analysis is image segmentation. Segmentation divides an image into its constituent parts. The degree of segmentation depends on the subject of interest. That is, when the objects of interest are separated from the background according to the user's needs, segmentation should stop. Generally, image segmentation is one of the most challenging stages of image processing. Broadly speaking, digital image segmentation can be divided into two categories based on color:

- Grayscale images
- Color images

In grayscale images, each pixel has a scalar value in the range [0,255]. Essentially, in these types of images, each pixel has only one dimension, which is the numerical value representing the gray level for that pixel.

However, in color images, each pixel has more than one dimension. For example, in the RGB color space, each pixel has three components: R, G, and B. Therefore, the color quality of each pixel is formed from the combination of these three components [3].

Color is a low-level feature of the image that has significant meaning in extracting homogeneous regions, often related to objects or parts of objects. In a 24-bit color image, the number of unique colors usually exceeds half the size of the image and can reach up to 16 million. Most of these colors are perceptually close and cannot be distinguished by the human eye. For all unique colors that are perceptually close, they can be combined into homogeneous regions, making the image more meaningful and easier to analyze. In image processing and computer vision, color image segmentation is a primary task for image analysis and pattern recognition. Image segmentation is a process of dividing an image into multiple regions, where these regions are considered homogeneous based on one or more characteristics.

Indeed, the first stage in image analysis is segmentation. Segmentation is the process of dividing an image into its main constituent parts. This means that different objects in the image are separated according to the intended application to facilitate further image analysis. Some practical applications of segmentation in image processing include automated tracking of moving targets in military applications and distinguishing different products in industrial applications. Figures 1 and 2 show examples of image segmentation.



**Fig. 2.** Segmented Image



**Fig. 1.** Original Color Image

Image segmentation is the process of assigning labels to pixels so that pixels with the same label share similar characteristics. Therefore, the goal of segmentation is to divide the input image into different regions such that pixels within a region are similar, and pixels from different regions are different.

### **3. PRELIMINARY DEFINITIONS AND CLUSTERING METHODS**

To analyze and evaluate data, we can use classification and clustering methods. In the context of fuzzy clustering, unlike classification, data points do not have labels, and clustering is performed unsupervised. In non-fuzzy clustering, each data point belongs to one cluster, but in fuzzy clustering, a data point may belong to multiple clusters. In fuzzy clustering, data points that are more similar to each other are grouped together, and the clusters are not mutually exclusive [11].

#### **3.1. Non-Fuzzy Clustering Method HCM**

One of the non-fuzzy clustering methods is the Hard C-Means (HCM) method, where data points must belong to only one cluster, and each cluster includes at least one and at most  $n-1$  data points. In other words, membership values only include 0 and 1,  $u_{ik} \in \{0,1\}$ ,  $1 \leq i \leq c$ ,  $1 \leq k \leq n$  where  $i$  represents the cluster and  $k$  represents the data point. Given the values of  $u_{ik}$  from the matrix  $U$ , we can determine that the  $k$ -th data point belongs to the  $i$ -th cluster [11].

In this method, we initially define an objective function that is the sum of the squared intra-group errors, and we attempt to minimize this objective (Equation 1):

$$v_i = \frac{\sum_{k=1}^n u_{ik} x_k}{\sum_{k=1}^n u_{ik}}, \quad J_w(U, V) = \sum_{k=1}^n \sum_{i=1}^c u_{ik} \|x_k - v_i\|^2 \tag{1}$$

where  $v_i$  represents the center of the  $i$ -th cluster, and  $\|x_k - v_i\|$  represents the distance of the  $k$ -th data point from the center of the  $i$ -th cluster. The closer the data point is to the center, the better the clustering. The center  $v_i$  is calculated as the average position of data points in the cluster, considering their membership values. If a data point does not belong to a cluster,  $u_{ik}=0$ , and it is not included in the calculation of  $\Sigma$ .

Another drawback of this method is that, in the best case, the clusters are spherical in shape, which in  $n$ -dimensional space translates to hyper-spheres because this method works with Euclidean distance [8].

### 3.2. Fuzzy Data Clustering (FCM)

One of the earliest fuzzy clustering methods, based on an objective function and utilizing Euclidean distance, was proposed by Dunn and later generalized by Bezdek. Yang conducted a comprehensive review of fuzzy clustering methods. Jajuga and Groenen introduced a fuzzy clustering model based on the second power root of the Minkowski distance, including both squared and non-squared Euclidean distances. The first fuzzy clustering algorithm utilizing second-order distances defined by a fuzzy covariance matrix was introduced by Gustafson and Kessel [9]. Further detailed studies on this initial algorithm were conducted by Kim and Krishnapuram. Babuska and colleagues improved the estimation of the fuzzy covariance matrix used in the Gustafson-Kessel (GK) algorithm. Subsequently, Nasraoui and Frigni presented a method based on the standard FCM algorithm to solve the problem of clustering and feature weighting simultaneously.

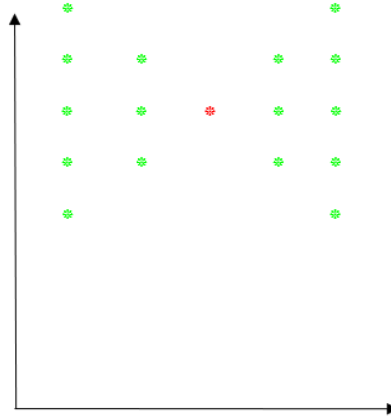
In the HCM clustering method, there was a problem with clustering data in the shape of butterflies (Figure 2), where the data was not correctly clustered. However, with the introduction of the FCM method, this problem was resolved. In the FCM algorithm, a data point can belong to multiple clusters, meaning that for a given data point, there are membership values rather than a single membership value. For butterfly-shaped data, the data point exactly in the middle is clustered such that it belongs to the first cluster with a membership value of 0.5 and to the second cluster with a membership value of 0.5.

In FCM, the distance of the data to the clusters is not important; what matters is the position of the data relative to the clusters. In some cases, it must be precisely determined which cluster a data point belongs to, which can be achieved using other algorithms. Clustering is appropriate when the data within a cluster are as close to each other as possible, and the centers of the clusters are as far apart as possible [13].

### 3.3. Objective Function of the FCM Algorithm

One of the most important and widely used clustering algorithms is the  $c$ -means algorithm. In this algorithm, samples are divided into  $c$  clusters, with the number  $c$  being predefined. In the fuzzy version of this algorithm, the number of clusters ( $c$ ) is also predefined. The objective function in the fuzzy  $c$ -means clustering algorithm is defined as follows (Zhao F, et al. 2016):

$$J_w(U, V) = \sum_{k=1}^n \sum_{i=1}^c u_{ik}^m d_{ik}^2 = \sum_{k=1}^n \sum_{i=1}^c u_{ik}^m \|x_k - v_i\|^2 \tag{2}$$



**Fig. 3.** Butterfly-like data [13]

In the above formula,  $m$  is a real number greater than one, typically chosen as two. If  $m$  is set to one, the objective function reduces to the non-fuzzy  $c$ -means clustering (classical) algorithm. In this formula,  $x_k$  represents the  $k$ th sample,  $v_i$  represents the center of the  $i$ th cluster, and  $n$  is the number of samples.  $u_{ik}$  denotes the membership degree of the  $k$ th sample in the  $i$ th cluster. The symbol  $\|x_k - v_i\|$  represents the similarity (distance) of the sample from the cluster center, which can be calculated using any function that indicates the similarity between the sample and the cluster center. From  $u_{ik}$ , a matrix  $U$  can be defined with  $c$  rows and  $n$  columns, where the components can take any value between zero and one. If all components of the matrix  $U$  are either zero or one, the algorithm would be similar to the classical  $c$ -means [10].

Since clustering is performed in a fuzzy manner, a data point can belong to multiple clusters, but the sum of the membership values for all clusters must equal one and should not exceed one (Equation 3). This is one of the conditions of the algorithm:

$$\sum_{i=1}^c u_{ik} = 1, \forall k = 1, \dots, n \tag{3}$$

The meaning of this condition is that the sum of the membership values for each sample in the  $c$  clusters must equal one. To derive the formulas for  $u_{ik}$  and  $v_i$  (Equations 4 and 5), we need to minimize the defined objective function. Using the above condition and setting the derivative of the objective function to zero, we have:

$$u_{ik} = \frac{1}{\sum_{j=1}^c \left(\frac{d_{ik}}{d_{jk}}\right)^{2/(m-1)}} = \frac{1}{\sum_{j=1}^c \left(\frac{\|x_k - v_i\|}{\|x_k - v_j\|}\right)^{2/(m-1)}} \tag{4}$$

$$v_i = \frac{\sum_{k=1}^n u_{ik}^m x_k}{\sum_{k=1}^n u_{ik}^m} \tag{5}$$

Using the above two formulas, the fuzzy  $c$ -means clustering algorithm is as follows.

### 3.4. Disadvantages of the FCM Algorithm

The FCM method has several disadvantages [13]:

1. This algorithm has a high computational cost.

2. It is sensitive to initial values of  $u_{ik}$ . If the initial  $u_{ik}$  values are close to a local minimum, the algorithm may be guided towards that local minimum [11].

3. It is sensitive to noise. Although this is not a major disadvantage and noise can be removed with preprocessing.

### 3.5. Performance Evaluation Criteria for the FCM Algorithm

Finally, after the algorithm stops, we can evaluate the results using performance criteria. By using an evaluation criterion, we can determine the optimal number of clusters. A good evaluation criterion usually has a single minimum point, which can be identified as the optimal point (Figure 3).

As an example of a good evaluation criterion, we can mention the Sugeno criterion, where the optimal cluster is the one with the lowest value, meaning the cluster whose function  $p(c)$  has the minimum value (Equation 6).

### 3.6. Fukuyama and Sugeno Evaluation Criterion

In formula 6,  $U_{ik}$  represents the membership degree of the  $k$ th data point to the  $i$ -th cluster,  $x_k$  is the  $k$ th data point,  $v_i$  represents the center of the  $i$ -th cluster, and  $\bar{X} = \frac{1}{n} \sum_{k=1}^n X_k$  is the number of clusters [2].

$$P(c) = \sum_{i=1}^c \sum_{k=1}^n U_{ik}^m (\|X_k - V_i\|^2 - \|V_i - \bar{X}\|^2) \tag{6}$$

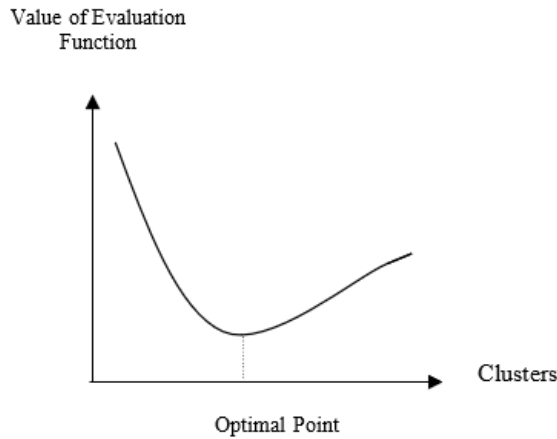


Fig. 4. Optimal cluster by evaluation criteria using evaluation criteria [2]

### 3.7. Using Fuzzy C-means Clustering for Image Segmentation

In this section, different image segmentation methods are described, and the advantages and disadvantages of each method are examined. Each segmentation method has its advantages; for example, some methods do not require the user to specify the number of regions in the image and operate unsupervised. Using spatial information of pixels (pixel neighborhood relationships) makes the segmentation algorithm more robust to noise and non-uniformities in the input image. Some image segmentation methods operate solely based on the similarity of features such as intensity, while others use spatial information in addition to intensity, color, texture, etc.

Segmentation approaches, due to their simplicity and effectiveness, were among the first techniques used for clustering natural images. The K-means clustering method (or Lloyd's algorithm, Lloyd 1982) and its fuzzy version, Fuzzy C-means, are some of the most common techniques used in clustering-based segmentation and are, generally, the most popular clustering algorithms used in industrial applications and machine learning [8].

However, despite its popularity, K-means suffers from three major drawbacks when it comes to segmenting textured color images [12]:

1. This algorithm uses an iterative procedure that might converge to a local minimum. This convergence to a poor local minimum can occur due to poor initializations (bad selection of initial cluster values) or the high complexity and dimensionality of the dataset (such as high-dimensional features required to describe color textures).
2. Most clustering methods perform segmentation only in feature space without considering spatial constraints, which significantly reduces the algorithm's performance in image segmentation.
3. Lastly, K-means is often incorrectly assumed to produce spherical clusters with equal volumes.

To overcome the sensitivity of the FCM algorithm to noise, Wei Yang proposed an extended FCM algorithm for image segmentation in 2007. The extended algorithm was developed by modifying the objective function of the standard FCM algorithm. In the extended algorithm, the influence of neighboring pixels on the central pixel is incorporated by adding a penalty term to the objective function of the standard FCM algorithm. In this method, the spatial dependency of a dataset is defined using a matrix  $W$ , where  $w_{ij}$  is one if data points  $x_i$  and  $x_j$  are adjacent and zero otherwise. The standard FCM algorithm does not utilize any spatial information; it clusters based only on pixel intensity levels, which makes it sensitive to noise. To incorporate neighborhood structure into the FCM algorithm, a penalty term is added to its objective function. The new objective function is presented below.

$$\sum_{k=1}^n \sum_{i=1}^c (u_{ik})^q \cdot d^2(x_k, v_i) + \gamma \sum_{k=1}^n \sum_{j=1}^n \sum_{i=1}^c (u_{ik}^q)(1 - u_{ij})^q w_{kj} \tag{7}$$

where  $w_{kj}$  is used to check the neighborhood relationship between  $x_j$  and  $x_k$ , and gamma adjusts the influence of the penalty term. The penalty term minimizes when the membership of a pixel and its neighboring pixels in a specific class is large and increases if the membership of a pixel in a class is high but its neighbors' membership in the same class is low. Essentially, the penalty term imposes a constraint on the similarity of the membership values of a pixel and its neighbors in one class. The penalized objective function can be minimized similarly to the standard FCM algorithm. An iterative algorithm is obtained by evaluating cluster centers and memberships to satisfy the zero-gradient condition. By applying the constraint that the sum of the memberships of a data point in all classes equals one, and by taking the partial derivative of the objective function and setting it to zero, a new expression for  $u_{ik}$  membership degree of the  $k$ th data point in cluster  $i$ ) is derived as follows [6]:

$$u_{ik}^* = \frac{1}{\sum_{l=1}^c \left( \frac{d^2(x_k, v_l) + \gamma \sum_{j=1}^n (1 - u_{lj})^q w_{jk}}{d^2(x_k, v_l) + \gamma \sum_{j=1}^n (1 - u_{lj})^q w_{jk}} \right)^{1/(q-1)}} \tag{8}$$

Similarly, by taking the partial derivative of the modified objective function with respect to  $v_i$  and setting the result to zero, the new center of the  $i^{\text{th}}$  cluster is obtained as:

$$v_i^* = \frac{\sum_{k=1}^n (u_{ik})^q x_k}{\sum_{k=1}^n (u_{ik})^q} \tag{9}$$

The steps of the proposed algorithm are as follows:

1. Set the parameters  $q$  (fuzzification parameter),  $c$  (number of clusters),  $\epsilon$ (threshold value), and  $v_i$  (cluster centers).
2. Calculate membership values using the proposed membership determination formula.
3. Calculate the new cluster centers.
4. Repeat steps 2 and 3 until convergence is achieved. When the algorithm converges, a defuzzification process is performed to convert the membership matrix  $U$  into a non-fuzzy segmentation of the data. The defuzzifier used here assigns the  $k$ -h data point to the cluster in which it has the highest membership value.

#### **4. CONCLUSION**

Today, segmentation is considered one of the most important stages in digital image processing. With technological advancements and the increasing practical use of computer programs in human life, the application and analysis of digital images are becoming more prominent. Image segmentation has numerous applications in various fields such as traffic management, medicine, weather forecasting, judiciary, and law enforcement. Given the importance of color in many contexts, color image segmentation has its own specific attractions and applications. One of the most common color spaces is the RGB color space, which is the nature of many images captured by modern media. One of the most successful methods in this study area is the clustering of digital image pixels. Among clustering methods, the fuzzy clustering algorithm can be considered an appropriate solution due to its high flexibility and use of fuzzy rules to better model uncertainties in pixel values.

Reviewing previous methods indicates that one effective approach in CT scan image segmentation is the use of clustering methods. Methods such as K-means and FCM have been used in this study area. The FCM method, relying on fuzzy techniques, is more flexible and precise compared to methods like K-means. However, a significant issue affecting the effectiveness of these methods is the accuracy of the initial cluster centers. In fact, clustering methods lack a clear idea for selecting appropriate initial values for clustering. However, if we can choose the initial cluster values well, we can expect effective performance from a method like FCM.

#### **Declaration**

We acknowledge that we used ChatGPT to enhance the academic writing of our manuscript while ensuring the originality and integrity of our work.

#### **Transparency Statement**

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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#### **Declaration of Interest**

The authors declare that they have no competing interests.

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