MEDICAL IMAGE SEGMENTATION USING ENHANCED K-MEANS AND KERNELIZED FUZZY C-MEANS

Gunwanti S. Mahajan¹, Kanchan S. Bhagat²

¹Dept of E&Tc, J.T.Mahajan C.O.E.North Maharasthra Univresity, Faizpur India
²Dept of E&Tc, J.T.Mahajan C.O.E.North Maharasthra Univresity, Faizpur India

ABSTRACT

Medical image segmentation is an initiative with tremendous usefulness. Biomedical and anatomical information are made easy to obtain as a result of success achieved in automating image segmentation. More research and work on it has enhanced more effectiveness as far as the subject is concerned. Several methods are employed for medical image segmentation such as Clustering methods, Thresholding method, Classifier, Region Growing, Deformable Model, Markov Random Model etc. This work has mainly focused attention on Clustering methods, specifically k-means and fuzzy c-means clustering algorithms. We have used the cluster centre initialisation algorithm in order to improve the performance of k-means and fuzzy C-means in addition with Kernelized fuzzy c-means and Enhanced k-means. Which has a better result in terms of silhouette score. The algorithms have been implemented and tested with Magnetic Resonance Image (MRI) images of Human brain. Results have been analyzed and recorded.

Keywords: Clustering algorithms, Enhanced k-means, Fuzzy c-means, K-means, Kernelized fuzzy c-means.

1. INTRODUCTION

Diagnostic imaging is an invaluable tool in medicine today. Magnetic Resonance Imaging (MRI), Computed Tomography, Digital Mammography, and other imaging modalities provide effective means for non-invasively mapping the anatomy of a subject. These technologies have greatly increased knowledge of normal and diseased anatomy for medical research and serves as a critical component in diagnosis and treatment planning[1].

Computer algorithms for the delineation of anatomical structures and other regions of interest are a key components assisting and automating specific radiological tasks. These algorithms are otherwise known as image segmentation algorithms. They are of great importance in biomedical
imaging applications like tissue volume quantification, diagnosis, localization pathology, study of anatomical structures[2], treatment planning, partial volume correction of functional imaging data and computer integrated surgery[3]. More research and work on it has enhanced more effectiveness as far as the subject is concerned. Several methods are employed for medical image segmentation such as Clustering methods, Thresholding method, Classifier, Region Growing, Deformable Model, Markov Random Model etc[4][5]. Specifically k-means and fuzzy c-means clustering algorithms.

K-means is a well known prototype-based, partitioning clustering technique that attempts to find a user-specified number of clusters (K), which are represented by their centroids. K-means is simple but it is quite sensitive to initial positions of cluster centres. Recently, fuzzy c-means of unsupervised clustering techniques used on established outstanding results in automated segmenting medical images in a robust manner[2]. Fuzzy c-means clustering[8] is successfully applied in many real world problems such as astronomy, geology, medical imaging, target recognition, and image segmentation. Among them, fuzzy c-means segmentation method has considerable benefits, because they could retain much more information from the original image than hard segmentation methods. But as we know that the clustering depends on choice of initial cluster centre hence we have used the cluster centre initialisation algorithm in order the improve the performance of k-means and fuzzy C-means in addition with Kernelized fuzzy c-means and Enhanced k means. The motivation for this work is to increase patient safety by providing better and more precise data for medical decisions. And also establish links and identify important and relevant medical problems.

Rest of paper is organized as (2) Related work, (3) Methodology includes different segmentation algorithms for medical resonance images that are K-means, Fuzzy c-means Kernelized fuzzy c-means, and Enhanced fuzzy c-means, (4) Results includes comparison of these four algorithm, (5) (6) Conclusion and Future work respectively.

2. RELATED WORK

Numerous methods are available in medical image segmentation. These methods are chosen based on the specific applications and imaging modalities. Imaging artifacts such as noise, partial volume effects, and motion can also have significant consequences on the performance of segmentation algorithms[3]. A novel initialization algorithm of cluster centres for K-means algorithm has been proposed by S. Deelers et al[7]. The algorithm was based on the data partitioning algorithm used for colour quantization. A given data set was partitioned into \( k \) clusters in such a way that the sum of the total clustering errors for all clusters was reduced as much as possible while inter distances between clusters are maintained to be as large as possible[7].

Keh-Shih Chuang et al[15] proposed spatial FCM that incorporates the spatial information into the membership function to improve the segmentation results. The membership functions of the neighbours centred on a pixel in the spatial domain are enumerated to obtain the cluster distribution statistics. These statistics are transformed into a weighting function and incorporated into the membership function. This neighbouring effect reduces the number of spurious blobs and biases the solution toward piecewise homogeneous labelling[15].

In Research of Shreyansh Ojha it has proven that the Enhanced k-means algorithm is better than the conventional K-Means Clustering Algorithm for colour image segmentation, the validity measure of nearly all the images has been better than the conventional K-Means clustering algorithm, the conventional K-means algorithm uses user defined number of cluster which use to cause noisy image, but in the proposed algorithm, it uses the method for determining the number of optimal cluster[16]. It also removes the problem of empty clusters problem from conventional K-Means clustering algorithm where there was issue that if no pixel is assigned to a cluster then that cluster remains empty[16].
3. METHODOLOGY

3.1. Segmentation using K-means Clustering

K-means is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters (assume k clusters) fixed a priori. The main idea is to define k centroids, one for each cluster. These centroids should be placed in a cunning way because of different location causes different result. So, the better choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given data set and associate it to the nearest centroids. When no point is pending, the first step is completed and an early groupage is done. At this point we need to re-calculate k new centroids as barycentres of the clusters resulting from the previous step. After we have these k new centroids, a new binding has to be done between the same data set points and the nearest new centroid. A loop has been generated. As a result of this loop we may notice that the k centroids change their location step by step until no more changes are done. In other words centroids do not move any more [5].

Finally, this algorithm aims at minimizing an objective function, in this case a squared error function. The objective function is given as

\[ J_k(U, V) = \sum_{i=1}^{k} \sum_{j=1}^{n} ||x_j - v_i||^2 \]  \hspace{1cm} (3.1.1)

Where \( ||x_j - v_i|| \) is a chosen distance measure between a data point \( X_j \) and the cluster centre \( V_i \), is an indicator of the distance of the \( n \) data points from their respective cluster centres.

3.2. Fuzzy C-means Clustering

Fuzzy c-means (FCM) is a method of clustering which allows one piece of data to belong to two or more clusters. This method was developed by Dunn in 1973 and improved by Bezdek in 1981 and it is frequently used in pattern recognition. The traditional FCM algorithm has been used with some success in image segmentation. The FCM algorithm is an iterative algorithm of clustering technique that produces optimal \( c \) partitions, centres \( V= \{v_1, v_2, ..., v_c\} \) which are exemplars, and radii which defines these \( c \) partitions. Let unlabelled data set \( X=\{x_1, x_2, ..., x_n\} \) be the pixel intensity where \( n \) is the number of image pixels to determine their memberships. The FCM algorithm tries to partition the data set \( X \) into \( c \) clusters [6]. The standard FCM objective function is defined as follows

\[ J_m(U, V) = \sum_{i=1}^{c} \sum_{k=1}^{n} u_{ik}^m ||x_k - v_i||^2 \]  \hspace{1cm} (3.2.1)

Where \( ||x_k - v_i||^2 \) represents the distance between the pixel \( x_k \) and centroid \( v_i \), along with constraint \( \sum_{i=1}^{c} U_{ik} = 1 \), and the degree of fuzzification \( m \geq 1 \). A data point \( x_k \) belongs to a specific cluster \( v_i \) that is given by the membership value \( U_{ik} \) of the data point to that cluster. Local minimization of the objective function \( J_m(U, V) \) is accomplished by repeatedly adjusting the values of \( U_{ik} \) and \( v_i \) according to the following equations[3].

\[ u_{ik} = \frac{(1-K(x_k,v_j))^{-1/(m-1)}}{\sum_{j=1}^{c}(1-K(x_k,v_j))^{-1/(m-1)}} \]  \hspace{1cm} (3.2.2)

\[ v_i = \frac{\sum_{k=1}^{n} u_{ik}^m K(x_k,v_i)x_k}{\sum_{k=1}^{n} u_{ik}^m K(x_k,v_i)} \]  \hspace{1cm} (3.2.3)
As $J_m$ is iteratively minimized, $v_i$ becomes more stable. Iteration of pixel groupings is terminated when the termination measurement $\max_{1 \leq i \leq c} \{\|V_i^t - V_i^{t-1}\|\} < \epsilon$ satisfied, where $V_i^t$ the new centre is and $V_i^{t-1}$ is the previous centre, and $\epsilon$ is the predefined termination criterion between 0 and 1. Finally, all pixels are distributed into clusters in which those cluster-centres and the fuzzy partition matrix $U_{c \times n}$ are gathered in the output as essential parameters to evaluate the performance of this clustering method.

With fuzzy $c$-means, the centroid of a cluster is computed as being the mean of all points, weighted by their degree of belonging to the cluster. The degree of being in a certain cluster is related to the inverse of the distance to the cluster. By iteratively updating the cluster centres and the membership grades for each data point, FCM iteratively moves the cluster centres to the "right" location within a data set. Performance depends on initial centroids there are various method proposed in the literature for the centre initialization will have presented the robust method for the cluster centre initialization.

### 3.3. Enhanced K-means

Although $K$-means is simple and can be used for a wide variety of data types, it is quite sensitive to initial positions of cluster centres. The final cluster centroids may not be optimal ones as the algorithm can converge to local optimal solutions. An empty cluster can be obtained if no points are allocated to the cluster during the assignment step. Therefore, it is quite important for $K$-means to have good initial cluster centres. The algorithms for initializing the cluster centres for $K$-means have been proposed a new cluster centre initialization algorithm. Hence the proposed enhanced k-means algorithm will be as follows.

#### 3.3.1. Enhanced k-means algorithm

1. Read the input image.
2. Decide the number cluster and initialize the cluster centre obtained from cluster centre initialization algorithm.
3. Partitioning the input data points into $k$ clusters by assigning each data point to the closest cluster centroid using the selected distance measure,
5. Re-computing the centroids.
6. If cluster centroids or the assignment matrix does not change from the previous iteration, stop; otherwise go to step 2.

### 3.4. Kernelized fuzzy C-means

In image clustering, the most commonly used feature is the gray-level value, or intensity of image pixel [13]. Thus the FCM objective function is minimized when high membership values are assigned to pixels whose intensities are close to the centroid of its particular class, and low membership values are assigned when the point is far from the centroid. From the discussion, we know every algorithm that only uses inner products can implicitly be executed in the feature space $F$. This trick can also be used in clustering, as shown in support vector clustering and kernel (fuzzy) $c$-means algorithms. A common ground of these algorithms is to represent the clustering centre as a linearly-combined sum of all $\Phi(x_k)$, i.e. the clustering centres lie in feature space. In this section, we construct a novel Kernelized FCM algorithm with objective function as following.

$$J_m(U, V) = \sum_{i=1}^{c} \sum_{k=1}^{n} u_{ik}^m \|\phi(x_k) - \phi(V_i)\|^2$$  \hspace{1cm} (3.4.1)
similar way to the standard FCM algorithm, the objective function \( J_m \) can be minimized under the constraint of \( U \). Specifically, taking the first derivatives of \( J_m \) with respect to \( u_{ik} \) and \( v_i \), and zeroing them respectively, two necessary but not sufficient conditions for \( J_m \) to be at its local extreme will be obtained as the following.

\[
\begin{align*}
    u_{ik} &= \left(1 - \frac{1}{1/(m-1)} \right) \\
    V_i &= \left(1/(m-1) \right)
\end{align*}
\]

(3.4.2)

Here we use only the Gaussian RBF kernel for the simplicity of derivation of the Eqs (3.4.2) and (3.4.3) and hence the algorithm in is just a special case of our algorithm. For other kernel functions, the corresponding equations are a little more complex, because their derivatives are not as simple as the Gaussian RBF kernel function.

3.4.1. Kernelized fuzzy C-means algorithm

The Kernelized fuzzy C-means algorithm includes the following steps:

Step 1: Get the data from Image.
Step 2: Fix the number of Clusters and assign the initial cluster centres using centre initialization algorithm.
Step 3: Compute partition matrix using (3.4.2).
Step 4: Update the cluster centres using (3.4.3).
Step 5: Repeat steps (3–4) until the following termination criterion is satisfied:

\[ \| V(\text{present}) - V(\text{previous}) \| < \varepsilon \]

where \( V(\text{present}) \) and \( V(\text{previous}) \) are the vector of cluster prototypes at present iteration and previous iteration.

4. RESULTS

The implemented clustering methods have been done in MATLAB. Three images acquired through Magnetic Resonance Imaging (MRI) were used for comparing the performances of the four methods. The benchmarks are used to compare: Silhouette score, Mean square error, Peak signal to noise ratio.

4.1. Silhouette score

Silhouettes are a general graphical aid for interpretation and validation of cluster analysis. This technique is available through the silhouette function (cluster package). In order to calculate silhouettes, two types of data are needed:

- The collection of all distances between objects. These distances are obtained from application of dist function on the coordinates of the elements in mat with argument method.
- The partition obtained by the application of a clustering technique. In sil.score context, the partition is obtained from the Kmeans function (amap package) with argument method which indicates the cluster to which each element is assigned.

For each element, a silhouette value is calculated and evaluates the degree of confidence in the assignment of the element:

- well-clustered elements have a score near 1,
- poorly-clustered elements have a score near -1.
4.2. Mean square error

In statistics, the mean squared error (MSE) of an estimator is one of many ways to quantify the difference between values implied by an estimator and the true values of the quantity being estimated. MSE is a risk function, corresponding to the expected value of the squared error loss or quadratic loss. MSE measures the average of the squares of the "errors." The MSE is the second moment (about the origin) of the error, and thus incorporates both the variance of the estimator and its bias. If \( \hat{Y} \) is a vector of n predictions, and \( Y \) is the vector of the true values, then the (estimated) MSE of the predictor is:

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} (\hat{Y}_i - Y_i)^2
\]  

(4.2.1)

4.3. Peak signal to noise ratio

PSNR is most easily defined via the mean squared error (MSE). Given a noise-free \( m \times n \) monochrome image \( I \) and its noisy approximation \( K \), MSE is defined as:

\[
MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i,j) - K(i,j)]^2
\]  

(4.3.2)

The PSNR is defined as:

\[
PSNR = 10 \cdot \log_{10} \left( \frac{MAX^2_I}{MSE} \right)
\]  

(4.3.3)

\[
PSNR = 20 \cdot \log_{10} \left( \sqrt{\frac{MAX^2_I}{MSE}} \right)
\]  

(4.3.4)

\[
PSNR = 20 \cdot \log_{10}(MAX_I) - 10 \cdot \log_{10}(MSE)
\]  

(4.3.5)

4.4. Segmentation results on MRI brain images using the different methods

K-means, Fuzzy c-means, kernelized Fuzzy-c-means and Enhanced k means have been used in segmenting three MRI images in order to compare the results in each case.

<table>
<thead>
<tr>
<th>Methods</th>
<th>Silhouette score</th>
<th>Mean square error</th>
<th>Peak signal to noise ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>K means</td>
<td>0.4748</td>
<td>43.8951</td>
<td>31.7066</td>
</tr>
<tr>
<td>F C- means</td>
<td>0.2136</td>
<td>78.3304</td>
<td>29.1915</td>
</tr>
<tr>
<td>Kernelized F C-Means</td>
<td>0.8922</td>
<td>48.4131</td>
<td>31.2812</td>
</tr>
<tr>
<td>Enhanced K -means</td>
<td>1</td>
<td>0</td>
<td>INF</td>
</tr>
</tbody>
</table>

Fig 1

Table -1 Comparison of segmentation results on Fig 1
Table -2 Comparison of segmentation results on Fig 2

<table>
<thead>
<tr>
<th>Methods</th>
<th>Silhouette score</th>
<th>Mean square error</th>
<th>Peak signal to noise ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>K means</td>
<td>0.4406</td>
<td>42.7262</td>
<td>31.8239</td>
</tr>
<tr>
<td>F C means</td>
<td>0.3950</td>
<td>11.4921</td>
<td>37.5268</td>
</tr>
<tr>
<td>Kernelized F C-Means</td>
<td>0.6018</td>
<td>27.1079</td>
<td>33.7998</td>
</tr>
<tr>
<td>Enhanced K -means</td>
<td>1</td>
<td>0</td>
<td>INF</td>
</tr>
</tbody>
</table>

Table-3 Comparison of segmentation results on Fig 3

<table>
<thead>
<tr>
<th>Methods</th>
<th>Silhouette score</th>
<th>Mean square error</th>
<th>Peak signal to noise ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>K means</td>
<td>0.4984</td>
<td>69.3533</td>
<td>29.7201</td>
</tr>
<tr>
<td>F C- means</td>
<td>0.2829</td>
<td>100.0876</td>
<td>28.1270</td>
</tr>
<tr>
<td>Kernelized F C-Means</td>
<td>0.6568</td>
<td>34.6928</td>
<td>32.7284</td>
</tr>
<tr>
<td>Enhanced K -means</td>
<td>1</td>
<td>0</td>
<td>INF</td>
</tr>
</tbody>
</table>

Fig 4 Graphical representation of silhouette score of all 3 images
5. CONCLUSION

By comparing the proposed methods Kernelized F C-means, and Enhanced K- means with established K-means and Fuzzy C-means, it is clear that our algorithms can segment MRI images much more accurately than the established algorithms. In other hand, the established Kernelized F C-means, and Enhanced K- means are much faster than the proposed methods for all tested data sets, due the proposed methods consume much time for obtaining the true number of segments. It is clear from calculating different parameters that from both proposed methods Enhanced K means is more accurate than Kernelized F C-means.

6. FUTURE WORK

Future research in MRI segmentation should strive toward improving the accuracy, precision, and computation speed of the segmentation algorithms, while reducing the amount of manual interactions needed. This is particularly important as MR imaging is becoming a routine diagnostic procedure in clinical practice. It is also important that any practical segmentation algorithm should deal with 3D volume segmentation instead of 2D slice by slice segmentation, since MRI data is 3D in nature.

7. REFERENCES

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