Image Segmentation of Medical Images using Automatic Fuzzy C-Mean Clustering

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Abstract— We presented a new method for image segmentation which is based on automatic fuzzy c-means clustering algorithm for medical images. It segments the image for better visibility. In the level set segmentation, the key curve is found via solving an optimization problem wherever a cost function is reduced, but its disadvantage of this technique is to fix iteration at the time of execution. In the proposed technique, there is no need to fix the iteration value, it takes automatically iteration value and segment the image. The experimental results show the best result in terms of normalized cross correlation, normalized absolute error and execution time. In the process of clustering, it partition the image into a number of clusters and give the segmented image.

Key words: Fuzzy c-means, Techniques, Spatial domain, level set method

I. INTRODUCTION

In the research community digital image processing is one of the most important areas for research. Image processing is a very [3] intellectual key that can modify outlooks of many designs. In digital image processing fundamental steps are image enhancement, image restoration, image acquisition, color edge processing, image compression, image segmentation and recognition. In today time [2] image segmentation plays an important role in many tasks. Image segmentation is the first step towards an attempt to analyze or interpret an image automatically. Segmentation provides bridges between low-level image processing and high-level image processing. An application involves for detection and recognition, make use of the image segmentation technique that provide measurement of object in the image. Application of segmentation includes Optical character recognition (OCR), Industrial inspection, Classification of terrains visible in satellite images, Tracking of objects in a sequence of images, Medical Image Detection their Measurement in bone, tissues and so on. Image segmentation is the feature of image processing. Image segmentation [4] is the process of grouping pixels of homogeneous regions by the use of the common feature approach. These features can be represented as space of color, texture and gray levels, each with the similarities between pixels of a region. In Image segmentation [1] dividing an image into many regions is the segmentation process. The objective of segmentation is to simplify the structure of an image that is more meaningful and easier to understand. Image segmentation is used where to point items and limitations (lines, curves, etc.) in images. In current time world computer vision has become an important field and is used in many applications like remote sensing, electronics, medical, etc. Recently Image segmentation is applied to Fuzzy set, rough set and in genetic algorithm and all of these gained much more attention. The output of image segmentation is obtained from entire cover image and is a set of many regions, or a locates of contours extracted as of the image. Each of the pixels in a region is similar with respect to some characteristic such as computed property, color, intensity, or texture.

FCM (Fuzzy c-means) is an unsupervised technique that has been successfully applied to future analysis, clustering, and classifier designs in the fields. An image can be represented in various feature spaces. The use of the Fuzzy segmentation method has gained more interest, which obtained additional information from the unique image than hard segmentation process (Bezdek et al. [7], Udupa et al. [8], Pham [9]). Fuzzy C means technique (FCM) can result a segmentation via fuzzy pixel classification. Apart from hard classification methods, where pixels only belong to one class exclusively, FCM allows multiple classes pixels with varying degrees of membership. This technique allows additional flexibility in application areas and has recently been used in processing of magnetic resonance image (MRI) [10].

II. RELATED WORK

Thord Andersson (2013) [11], in this method, level set methods is used to resolve the image segmentation problem. The result contour is found by finding an optimization problem where a cost function is minimized. Gradient descent methods are often used to explain this optimization difficulty since they are very simple to execute and applicable to general non convex functions. Conventionally, cost functional has been customized to evade these troubles. In this paper, it proposed two modified gradient descent methods, one is momentum term and another is on resilient propagation. These methods are normally used in the machine learning community. In a series of 2- D/3-D- experiments using real and synthetic data with positional truth, the modifications are shown to decrease the compassion for local optima and to enlarge the convergence rate.

Xing Zhang (2014) [12], central of human experience is Facial expression. The main issue is efficiency and valid measurement that automated facial image inquiry seeks to the location. Posed and un-posed facial expressions differ along several dimensions in which including timing and including complexity, well-annotated video of un-posed facial behavior is needed.

Haida Liang (2014) [13], Portable Remote Imaging System for Multispectral Scanning (PRISMS) is created for in situ 3D topographic imaging of wall paintings and, high resolution spectral and another huge plot. In this they transverse the resolution of an image at tens of microns, from tens of meters distances remotely, and creating a high resolution image, which is likely from a fixed position on
the ground in areas at heights that is challenging to access. A fully automated spectral imaging system, giving 3D topographic mapping at millimeter accuracy as a by-product of the image focusing process.

Feng Zhao (2013) [14], in this paper, it described about Image segmentation, where partitioning an image into a partial amount of semantically non-overlapping area. In medical applications, it is a basic course in nearly all systems that hold up medical diagnosis, and treatments. Normally, this procedure is done by hand via clinicians, which may be time-consuming and monotonous. To ease the difficulty, a figure of interactive segmentation ways has been planned in the literature. This method take benefit of mechanical segmentation. This paper presented a general idea of interactive segmentation techniques for medical images. Edge-based and region-based level set segmentation methods provide a direct way to estimate the geometric properties of anatomical structures.

III. PROPOSED METHODOLOGY

A. Automatic Fuzzy C Means Clustering Algorithm

The AFCM (Automatic Fuzzy C-Means) algorithm is most widely technique in image segmentation. Because it obtained more information in comparison to hard segmentation methods. In AFCM algorithm, the statistical patterns may fit into several clusters, having unusual membership values. The membership value of a statistic to a gather denotes the comparison between the given statistical model of the bunch. At certain set of n statistics patterns (i.e. \( X= [x_1, x_2, ..., x_n] \)), AFCM clustering algorithm is used to minimization of the following objective function \( R(U,C) \) AFCM by an iterative process [17];

\[
R_{FCM}(U,C) = \sum_{k=1}^{n} \sum_{i=1}^{n} (u_{ik})^m d^2(x_k, c_i) \tag{1}
\]

Where \( k \) is the \( k \)th d- data dimensional vector, \( i \) the center of the cluster \( i \), \( u_{ik} \) is the degree of membership of \( k \) in the \( i \)th cluster, exponent, \( m \) the weighting, \( x \) in the \( i \)th cluster, exponent, \( c \) the distance between data \( x \) and cluster \( i \) \( c \), \( n \) is the number of data patterns. The minimization of the objective function \( R(U,C) \) AFCM is attained by an iterative procedure

\[
u_{ik} = \frac{1}{\sum_{l=1}^{n} (d_{ik}/d_{il})^m} \tag{2}
\]

And

\[
c_i = \frac{\sum_{k=1}^{n} (u_{ik})^m x_k}{\sum_{k=1}^{n} (u_{ik})^m} \tag{3}
\]

Where \( \forall \, i \, u_{ik} \in [0,1], \forall k \sum_{i=1}^{n} u_{ik} = 1 \) and \( 0 < \sum_{k=1}^{n} u_{ik} < n \).

The clustering is a two-step method at each iteration. In the first step, it is the same as that in standard automatic FCM to compute the relationship job in the phantom domain. In the second step, the relationship information of every pixel is on to the spatial domain. The AFCM iteration starts with then overlap relationship that is incorporated with the special purpose. The iteration is closed when the maximum divergence between two cluster centers at two consecutive iterations is a smaller amount than a threshold. The following are the convergence, defuzzification is practical to assign every pixel to an exact cluster for which the membership is maximal.

1) Read Original Image

Fig. 1: Original Image

2) Display Original Image in Clustered Form

Fig. 2: Cluster Image1

Fig. 3: Cluster Image2

Fig. 4: Cluster Image3
first clustering center on the basis of minimum values of the image.
6) Find new Fuzzy clustering centers on the basis of first centers.
7) Find membership value for final clustering centers.
8) Find the matrix of final cluster centers where each row gives the center coordinates and final fuzzy partition matrix.
9) Find pixel intensity for intermediate images.
10) Calculate Normalized cross correlation between original image and segmented image for brightness quality.
\[
\text{NCC}_{\text{FCM}} = \frac{\text{sum}(\text{sum}(0_{\text{img}}X\text{Seg}_{\text{img}})))}{\text{sum}(\text{sum}(0_{\text{img}}X0_{\text{img}})))}
\]
11) Calculate Normalized Absolute Error between original image and segmented image.
\[
\text{NAE}_{\text{FCM}} = \frac{\text{sum}(\text{sum}(\text{abs(error)})))}{\text{sum}(\text{sum}(0_{\text{img}})))}
\]

V. Result Analysis

<table>
<thead>
<tr>
<th>Original Image</th>
<th>Final Segmented Image (Proposed)</th>
<th>Final Segmented Image (Base)</th>
</tr>
</thead>
<tbody>
<tr>
<td><img src="image1.png" alt="Image 5: Cluster Image4" /></td>
<td><img src="image2.png" alt="Cluster Image4" /></td>
<td><img src="image3.png" alt="Cluster Image4" /></td>
</tr>
<tr>
<td><img src="image4.png" alt="Image 6: Cluster Image5" /></td>
<td><img src="image5.png" alt="Cluster Image5" /></td>
<td><img src="image6.png" alt="Cluster Image5" /></td>
</tr>
<tr>
<td><img src="image7.png" alt="Image 7: Segmented Image" /></td>
<td><img src="image8.png" alt="Segmented Image" /></td>
<td><img src="image9.png" alt="Segmented Image" /></td>
</tr>
</tbody>
</table>

Table 1: Quantitative results for 5 standard images:

<table>
<thead>
<tr>
<th>Image</th>
<th>NCC&lt;sub&gt;FCM&lt;/sub&gt;</th>
<th>NAE&lt;sub&gt;FCM&lt;/sub&gt;</th>
<th>Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MO11.jpg</td>
<td>0.6577</td>
<td>0.7980</td>
<td>31.4587</td>
</tr>
<tr>
<td></td>
<td>1.0437</td>
<td>1.5315</td>
<td>2.3807</td>
</tr>
</tbody>
</table>
Table 2: AFCM Results (Proposed)

Table 2 shows the result of normalized cross correlation ($NCC_{FCM}$) give better results in comparison base results. We reduce normalized absolute error ($NAE_{FCM}$) and execution time. Table 3 shows inferior results as compare to the proposed method in terms of these parameters.

<table>
<thead>
<tr>
<th>Image</th>
<th>$NCC_{FCM}$</th>
<th>$NAE_{FCM}$</th>
<th>Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MO11.jpg</td>
<td>0.9062</td>
<td>0.3175</td>
<td>111.93</td>
</tr>
<tr>
<td>heart_ct.bmp</td>
<td>0.8493</td>
<td>0.2792</td>
<td>3.7420</td>
</tr>
</tbody>
</table>

Table 3 Base Results

<table>
<thead>
<tr>
<th>Image</th>
<th>$NCC_{FCM}$</th>
<th>$NAE_{FCM}$</th>
<th>Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>syn_16_20_3.bmp</td>
<td>0.4479</td>
<td>0.5531</td>
<td>92.2942</td>
</tr>
<tr>
<td>syn_new_9.bmp</td>
<td>0.1866</td>
<td>0.8047</td>
<td>93.6072</td>
</tr>
<tr>
<td>myBrain_axial.bmp</td>
<td>0.7780</td>
<td>0.2206</td>
<td>6.0856</td>
</tr>
</tbody>
</table>

VI. CONCLUSION

In this paper, we concluded image segmentation of medical images using automatic fuzzy c-means clustering technique.

In this method, we partition the image into a number of clusters for showing hidden part of an image. In the experimental results, we increased brightness of an image in terms of normalized cross correlation ($NCC_{FCM}$) and decreased execution time. In this paper, we concern an extended automatic FCM method so as incorporates the spatial information into the relationship function to get better the results of medical image segmentation.
REFERENCES


