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RESEARCH ARTICLE

Medical Image Segmentation Based on Improved Fuzzy Clustering Algorithm with Bias Field Estimation

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ABSTRACT: Medical image segmentation is difficult in image processing. There are lot of problem are occur in the real world images. In this paper, we provide an approach bias field estimation based fuzzy clustering method. Bias field estimation Useful in scan corrupted by salt and paper noise .The method follows a simple and easy way to classify a given data set through a certain number of clusters fixed a priori. In this project, Bias field estimation and segmentation of brain MR images we implemented the fuzzy clustering algorithm. This paper evaluates the ability of FCM to segment Gray Matter , White Matter . So that, Fuzzy C-means is an overlapping clustering algorithm. The advantages of the method are its clarity, efficiency, and self-organization. It is used as beginning process in many other algorithms. The experimental evaluation of fuzzy clusyering and FCM, with bias field estimation is performed in Matlab.

Keywords: bias field estimation, fuzzy c means, improved fuzzy clustering algorithm

1 Introduction

Medical imaging of internal organs of the human body is important to improve medical diagnosis and therapy. image segmentation is a major task in medical imaging. Due to poor resolution and weak enhanced contrast this task is difficult in the presence of noise and artifacts [1]. Many existing methods for segmentation are based on image intensity information, shape properties or shape prior[1],[2], [3], [4].M. Suzuki et al. [5] propose abdominal multi-organ segmentation with analyses of missing organs using statistical location model. A. Shimizua et al. [6] propose simultaneous extraction of multiple organs from abdominal CT using abdominal cavity standardization process with feature database and atlas guided segmentation incorporating parameter estimation for organ segmentation. M. G.Linguraru et al. [7] propose multi-region segmentation using graph cut method for four abdominal organ segmentation. T. Kohlberger et al. [8] propose multiorgan segmentation from CT medical images using learning-based segmentation and shape representation. Okada et al. [9] propose multi-organ segmentation based on hierarchical spatial modeling of organ interrelations using atlas information. Image segmentation is one of the most interesting and challenging problems in computer vision generally and medical imaging applications particularly. Segmentation partitions an image area or volume into non overlapping, connected regions, being homogeneous with respect to some signal characteristics (10). Segmentation approaches are subject to multiple challenges stemming from image noise, image artifacts such as partial volume effect, and discontinuities of edges and boundaries due to similar visual appearance of adjacent brain structures. A variety of segmentation methods techniques have been developed to address these challenges. Brain MR image segmentation methods can be classified into three main categories: probabilistic and statistical-based, atlas-based, and deformable model-based techniques.

2. Related work

2.1Image segmentation:

Image segmentation plays a crucial role in numerous biomedical imaging applications, assisting technicians or health care professionals during the diagnosis of various diseases. A new fuzzy level set algorithm is proposed in this paper to facilitate medical image segmentation which is able to directly evolve from the initial segmentation of spatial fuzzy clustering. The Spatial induced fuzzy c-means using pixel classification are utilizing dynamic variational boundaries for image segmentation. The controlling parameters of level set evolution are also estimated from the results of clustering. The fuzzy level set algorithm is enhanced with locally regularized evolution. Such improvements facilitate level set manipulation and lead to more robust segmentation. Performance evaluation of the proposed algorithm was carried on medical images from different modalities.

Panda et al. (11) tested the performances FCM and k-Means. Two distance measures such as Manhattan (MH) and Euclidean (ED) are used to note how these distance measures influence the overall clustering performance. The performance has been compared based on seven parameters, sensitivity, specificity, precision, accuracy, run time, average intra cluster distance and inter cluster distance. Based on the experimental results, the paper concluded that both k-Means and FCM performed well.

2.2Cluster Validity Functions :

One of the fundamental challenges of clustering is how to evaluate results, without auxiliary information. A common approach for evaluation of clustering results is to use validity indexes. Clustering validation is a technique to find a set of clusters that best fits natural partitions (number of clusters) without any class information.
Generally speaking, there are two types of clustering techniques, which are based on external criteria and internal criteria.

• External validation: Based on previous knowledge about data.

• Internal validation: Based on the information in trinsicto the data alone.

Considering these two types of cluster validation to determine the correct number of groups from a dataset, one option is to use external validation indexes for which a priori knowledge of dataset information is required, but it is hard to say if they can be used in real problems. Another option is to use internal validity indexes which do not require a priori information from dataset.

3.Our Contribution

The fuzzy clustering based on image intensity is done by the initial segmentation. Which employ the via field estimation method for object refinement by tracking the boundary variation the widely used conventional fuzzy c means for medical image segmentation is squared norm disatnce measure to measure the similarity between center and data object of medical image which are reduced by the heavy noise outliers and other imaging artifact.The contribution of our approach is bias field estimation and fuzzy clustering method. Fuzzy clustering plays an important role in solving problems in the areas of pattern recognition and fuzzy model identification. A different kinds of fuzzy clustering methods have been proposed and most of them are based upon distance criteria [12].bias field estimation Useful in scan corrupted by salt and paper noise One widely used algorithm is the fuzzy c-means (FCM) algorithm. Bias field estimation and segmentation the edge from blurring and Time consuming It uses reciprocal distance to compute fuzzy weights.
The proposed method for improved fuzzy clustering the algorithms were established for segmentation. The proposed method is done by filtering.

 Noises are reduced.

 The proposed method uses the improved fuzzy c-means algorithms which are very accurate to detect the tumor affected area in medical image segmentation

 It shrinks the time for analysis.

3.1Fuzzy c means clustering:

Fuzzy c-means (FCM) is a method of clustering [5] which allows one piece of data to belong to two or more clusters.The Fuzzy C-Means (FCM) clustering algorithm was first introduced by Dunn and later was extended by Bezdek. The algorithm is an iterative clustering method that produces an optimal c partition by minimizing the weighted within group sum of squared error objective

$$Y_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} \left\| X_i - C_j \right\|^2.$$

where X = {x1, x2, ・ ・ ・, xn} is the data set in the p-dimensional vector space, n is the number of data items c is the number of clusters with $2 \leq c < n$, uik is the degree of membership of xk in the ith cluster q is a weighting exponent on each fuzzy membership vi is the prototype of the centre of cluster id2 (xk, vi) is a distance measure between object xk and cluster centre vi.

3.2Improved the fuzzy clustering algorithm:

Intensity with respect to fuzzy membership '*U*', and set of cluster centroids, '*V*'.

$$J_m(U,V) = \sum_{j=1}^{N} \sum_{i=1}^{C} u_{ij}^{m} d^2(x_j, v_i)$$

…………………………………(Historically, the FCM clustering algorithm introduced by Bezdek is an improvement of earlier clustering methods . In these methods, it is assumed that number of clusters four, which are: background, gray matter, white matter, background belong to same class and as a result, number of classes reduces to three. The FCM algorithm is based on minimizing an objective function, with respect to fuzzy membership *ui*j for feature vector *xi* to *j-th* cluster, and *j-th* cluster centroids *θj*

$$J_q = \sum_{i=1}^{n} \sum_{j=1}^{m} u_{ij}^{q} d(x_i, \theta_j) \qquad (1)$$

In the above equation, m is number of clusters, n is number of feature vectors (pixel numbers in the image that represent the pixel's 1)

In (1) $X = \{x_1, x_2, \ldots. x_j \ldots x_N\}$ is a $p \times N$ data matrix, where, p represents the dimension of each x_j " distinctive feature" vector, and N represents the number of feature vectors (pixel numbers in the image). 'C' is the number of clusters. $U_{ij} \subseteq U(p,N,C)$ is the membership function of vector x_j to the ith cluster, which satisfies $u_{ij} \in [0, 1]$ .The mean intensity of tissue classes for initializing both FCM and k-Means is derived from a histogram guided method. In histogram guided initialization, let μ be the vector of mean intensity of 'k' tissue classes present in the pre-processed image,

$\mu = \{\mu 1, \mu 2, \mu 3 \ldots . \mu k\}$

and 'j' be an arbitrary sequence

$j = \{0, 1, 2, 3 \ldots . k\}$

The range of pixel intensities or the interval between maximum and minimum intensities in the pre-processed MR image is divided into 'k' intensity bins, with $k+1$ intensity points between the maximum and minimum intensity.MR image formation with multiplicative bias and additive noise:

$I = bJ + n,$ (1)

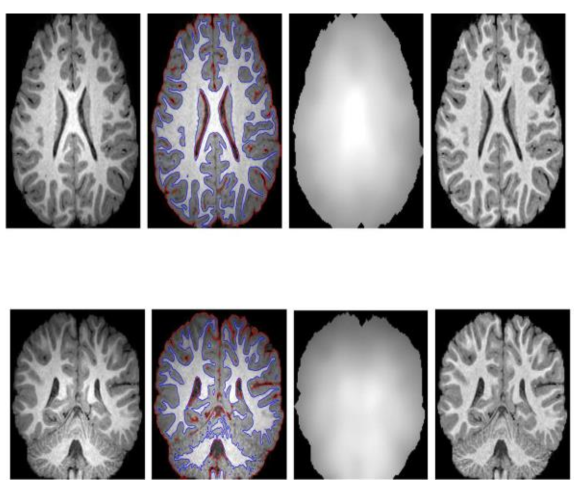
where I is the measured image intensity, J is the true signal to be restored, b is an unknown bias field, and n is additive noise. The goal of bias corrupted is to estimate the bias field b from the measured intensity I. New approach improver fuzzy c-mean (IFCM) [22] and define dissimilarity function as below:

$$\theta_j = \sum_{i=1}^{N} u_{ij}^q x_i \Bigg/ \sum_{i=1}^{N} u_{ij}^q \qquad (5)$$

where *(aj, bj) j-th* pixel's location. Magnitudes of two parameters λ and ζ are between [0, 1]; adjust the degree of the two neighborhood attractions. For any input image, defining an objective function and using an ANN, constant parameters λ and ξ are computable.

4. Experimental result

In this section, we focus on the application of the proposed method to segmentation and bias correction of brain MR images. We first show the results for 3T MR images in the first column of Fig. 1. These images exhibit obvious intensity inhomogeneities.The segmentation results, computed bias fields,bias corrected images, are shown in the second, third, and four column respectively. It can be seen that the intensities with in each tissue become quite homogeneous in the bias corrected images.The improvement intensity homogeneity can be also demonstrated by comparing the histogram of the original images and the bias corrected images.The histograms of the original images (left) and the bias corrected mages (right) are plotted in the fifth column. There are three well-defined and well-separated peaks in the histograms of the bias corrected image, each corresponding to a tissue or the background in the image. In contrast, the histograms of the original images do not have such well-separated peaks due to the mixture of the intensity distribution caused by the bias.Our method has also been tested on 7T MR images with promising results. At 7T, significant gains in image resolution can be obtained due to the increase in intensity level and reduce the noises. However, susceptibility-induced gradients scale with the main field, while the imaging gradients are currently limited to essentially the same strengths as used at lower field strengths(i.e., 3T). Such effects are most pronounced at air interfaces, This appears as a highly localized and strong bias, which is challenging to traditional methods. The result for this image shows the ability of our method to correct such bias, as shown in Fig. 2(b) and (c).



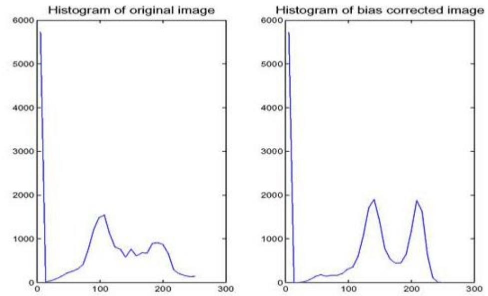


Fig. 1. Applications of our method to 3T MR images. Column 1: Original image; Column 2: Final zero level contours of □ (red) and □ (blue), i.e. the segmentation result; Column 3: Estimated bias fields; Column 4: Bias corrected images with fuzzy clustering; Column 5: Histograms of the original images (left) and bias corrected images (right).

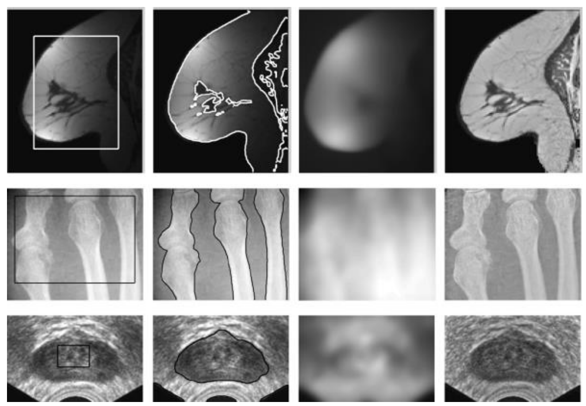


Fig. 2. Applications of our method to an MR image of breast, an X-ray image of bones, and an ultrasound image of prostate. Column 1: Initial contour on the original image; Column 2: Final contours; Column 3: Estimated bias field;Column 4: Bias corrected image

5. Conclusion

We propose to use fuzzy clustering method in medical image segmentation for fuzzy clustering with bias field estimation . The FCM algorithm uses reciprocal distance to compute the fuzzy weights.bias field estimation and segmentation Useful in scan corrupted by salt and paper noise. It provides more potentialfor effectively segmenting MRI data and time consuming. Gaussian weights reflect the distribution of the feature vectors in the clusters. several experiments using both medical image and general images demonstrate the advantages of our method. Pattern recognitions, Classification analysis, Artificial intelligence, image processing, machine vision, and many others. our method in terms of accuracy, efficiency, and robustness.As an application, our method has been applied to medical images with promising results.

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