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Segmentation of Brain MRI Images by Using Modified Robust Fuzzy c Means Algorithm

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Abstract: Image segmentation play a vital role in numerous biomedical imaging applications. Some of them are computer-integrated surgery, study of anatomical structure and quantification of tissue volumes. When compared to all other medical imaging techniques, the Magnetic Resonance Imaging (MRI) has received much attention because of its advantages. The MRI analysis involves a huge amount of data and hence it consumes time, labor when compared with manual segmentation. Further, the manual segmentation requires a high level of expertise in neuro anatomy and sometimes it leads to human error. To produce more robust segmentation in medical images, this paper presents a Modified Robust Fuzzy c-Means with weight Bias Estimation method. Further to reduce the number of iteration of the proposed method, this paper initializes the initial centroids of clusters using dist-max initialization method.

Key words: Brain MRI · Fuzzy c means

INTRODUCTION

Image segmentation is the process of by which a label can be allotted to each pixel in an image so that pixels with the same label have certain similar visual characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic (s). When applied to a stack of images, typical in Medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like Marching cubes.

A central problem, called segmentation, is to distinguish objects from background [1]. For intensity images (ie, those represented by point-wise intensity levels) four popular approaches are: threshold techniques, edge-based methods, region-based techniques and connectivity-preserving relaxation methods.

Threshold techniques, which make decisions based on local pixel information, are effective when the intensity levels of the objects fall squarely outside the range of levels in the background. Because spatial information is ignored, however, blurred region boundaries can create havoc. Edge-based methods center around contour detection: their weakness in connecting together broken contour lines make them, too, prone to failure in the presence of blurring.

Computational geometry provides several tools (for instance, hand probing, Monge matrix searching) that lead to efficient solutions for optimal segmentation, as long as one is only interested in separation of an object defined by monotone chains. Without such assumptions the problem is NP-hard and efficient heuristics remain to be found.

Discriminant analysis has also been applied successfully to the problem of transforming an intensity image into a binary black white picture. This line of research relates directly to what has long been an active line of research in computational geometry, point clustering: Partition a set of points into clusters so that some inter-cluster criterion is minimized. Segmentation can be defined as a collection of methods allowing to interpret spatially close parts of the image as objects. Regions (i.e., compact sets) represent spatial closeness naturally and thus are important building steps towards

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segmentation. Objects in a 2D image very often correspond to distinguishable regions.

The object is everything what is of interest in the image (from the particular application point of view). The rest of the image is background. The approach is similar to that used in pattern recognition, i.e., division of the image into set of equivalence classes. Segmentation is mostly based on rather ad hoc methods. There is no encompassing broad theory of segmentation. However, several recent theoretically grounded approaches have formulated segmentation as an optimization task. The special case of foreground vs. background segmentation is often met. Segmentation usually makes sense in a scope of a particular application.

Complete Segmentation: It divides an image into non-overlapping regions that match to the real world objects. Complete segmentation divides an image *R* into the finite number *S* of regions *R*1,..., *RSPartial* segmentation: It is possible to find only parts with semantic meaning in the image (e.g., regions, collection of edgels) which will lead to interpretation in later analysis.

Cluster analysis or clustering is the assignment of a set of observations into subsets (called *clusters*) so that observations in the same cluster are similar in some sense. Clustering is a method of unsupervised learning and a common technique for statistical data analysis used in many fields, including machine learning, data mining, pattern recognition, image analysis, information retrieval and bioinformatics. Besides the term clustering, there are a number of terms with similar meanings, including automatic classification, numerical taxonomy, botryology andtypological analysis.

Hierarchical algorithms find successive clusters using previously established clusters. These algorithms usually are either agglomerative ("bottom-up") or divisive ("top-down"). Agglomerative algorithms begin with each element as a separate cluster and merge them into successively larger clusters. Divisive algorithms begin with the whole set and proceed to divide it into successively smaller clusters.

Partitional algorithms typically determine all clusters at once, but can also be used as divisive algorithms in the hierarchical clustering.

Many clustering algorithms require the specification of the number of clusters to produce in the input data set, prior to execution of the algorithm. Barring knowledge of the proper value beforehand, the appropriate value must be determined, a problem on its own for which a number of techniques have been developed.

MATERIALS AND METHODS

Bias-Field Estimation: There are commonly substantial artifacts in real MR images, such as image nonuniformities caused by inhomogeneities in the B1or B0 fields, especially in high field (e.g. 3T) MR images. The intensity inhomogeneity may severely challenge quantitative image analysis algorithms, such as those used for image segmentation and registration. Intensity inhomogeneities are particularly severe in MRI at ultra-high field strengths (e.g. 7T) and sometimes make it difficult even for expert human observers to view the images.

It is commonly assumed that intensity in homogeneities can be ascribed to a spatially varying field that is a multiplicative component of the measured image. This multiplicative component, known as a *bias field*, varies spatially because of inhomogeneities in the B0 and B1 fields. *Biasfield correction* refers to a procedure to estimate the biasfield from the measured image so that its effect can be eliminated. There are two main types of methods for bias correction: prospective and retrospective methods. Prospective methods aim to avoid intensity inhomogeneities in the image acquisition process.These methods, while capable of correcting intensity inhomogeneity induced by the imaging device, are not able to remove object-induced effects. In contrast, retrospective methods are only on the information in the acquired images and thus they can remove intensity inhomogeneities regardless of their sources. Retrospective methods include those based on filtering [1-4], surface fitting [5-8], histogram [9, 10] and segmentation [11-17]. Most slowly varying).

The smoothness of the bias field is not only consistent with its physical origins in the MR imaging process, but also necessary to make the bias field correction problem tractable. However, the bias fields computed by direct implementation of most of the well-known methods are in general not smooth. This then requires an extra effort to maintain the smoothness of the computed bias field, which is often performed in an ad-hoc manner.

For example, in the method of Wells *et al.*an extra step of moving-average low pass filtering is introduced to smooth the computed bias field. In the method proposed by Sled *et al*, the estimated bias field has to be replaced by a linear combination of smooth B-spline basis functions to generate a smooth field. Pham and Prince proposed an energy minimization method for adaptive segmentation and estimation of the bias field.

The smoothness of the bias field is ensured by adding a smoothing constraint term into the energy in their method.

However, this introduces a highly computationally expensive procedure to solve a space-varying difference equation for a smooth bias field. In parametric methods, which model the bias field as a linear combination of polynomial basis functions, the computed bias field is always smooth. However, such parametric methods are not able to capture bias fields that cannot be well approximated by polynomials. Among retrospective methods, segmentation-based approaches are particularly attractive, as they unify the tasks of segmentation and bias correction into a single framework [18].

Segmentation-based methods have been one of the most popular type of bias correction methods according to a recent review by Vovk*et al.* In these methods, segmentation and bias field estimation are interleaved to benefit each other, thereby allowing both to be refined iteratively until convergence to an optimal solution [19].

In this process, the segmentation is usually achieved by using maximum likelihood or maximum a posteriori based methods. An important characteristic of local image intensities the intensities of various tissues within a each neighborhood form separable clusters and the center of each cluster can be well defined by the product of the bias within the neighborhood and a tissue-dependent constant. This characteristic provides an effective metric to evaluate the classification of the tissues and the estimation of th e bias field in terms of a *coherent local intensityclustering (CLIC)* criterion function. This CLIC criterion is an energy on a bias field [20].

Centroid Of Cluster Updating: Cluster unit-A unit in a competitive layer of a neural net is a self organizing net such as ART or SOM or a hidden unit in a counter propagation net.

Clustering-Grouping of similar patterns together. A clustering is a set of clusters. Cluster Analysis-Finding groups of objectssuch that the objects in a group will be similar (or related) to one another and different from (or unrelated to) the objects in other groups [21].

Membership Evaluation: We minimize the objective function subject to the constraints $\sum_{i=1}^{c} uik = 1$ using the Lagrange multiplier method.

$$L(U,V,\beta) = \sum_{i=1}^{c}\sum_{k=1}^{n} u_{ik}^{n} \left\| yk - \omega k \beta k - u_i \right\|^2 + \dot{x}\left(1 + \sum_{i=1}^{c} u_{ik}^{m}\right) + \lambda\left(1 - \sum_{i=1}^{c} u_{ik}\right)$$

Dist-Max Initialization Algorithm: To Find the distance matrix between the elements within each group. Select maximum distance from each distance matrix of groups.

Algorithm for the Proposed Method:

- Select the number of Clusters and initialize the centroid using *dist-max Initialization Algorithm.*
- Compute the membership.
- Update the centroid of the clusters
- Update the bias field
- Repeat steps 2-4 until termination.

Simulation Results

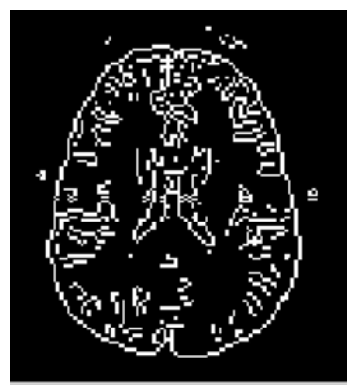

Fig. 1: Binary gradient image

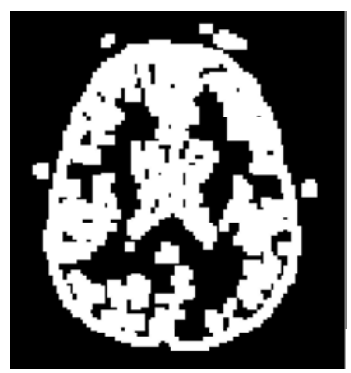

Fig. 2: Dilated gradient image

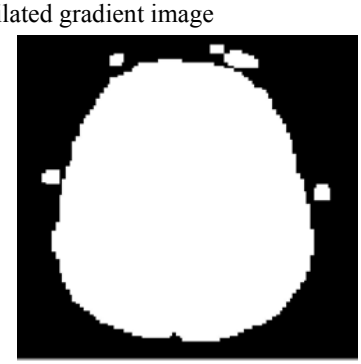

Fig. 3: Binary image with filled holes

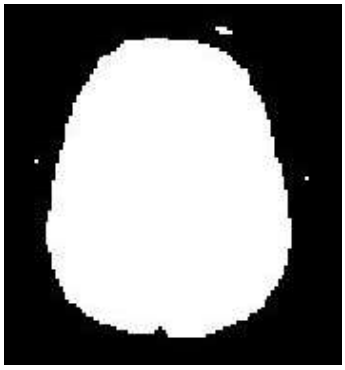

Fig. 4: Segmented image

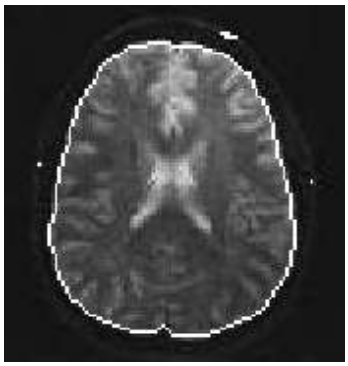

Fig. 5: Outlined original image

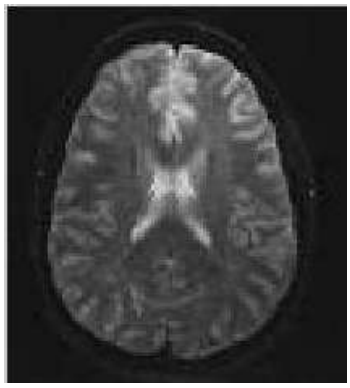

Fig. 6: Original Image

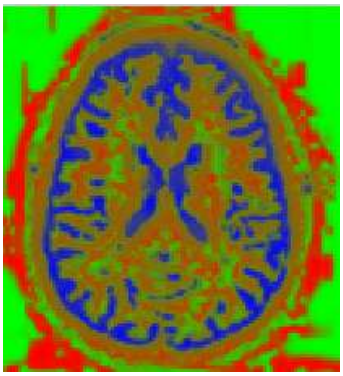

Fig. 7: Partitioned Matrix

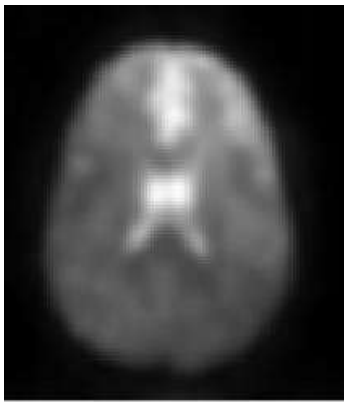

Fig. 8: Estimated bias field

Fig. 9: Corrected image

CONCLUSION

A modified robust fuzzy *c*-means algorithm for brain MR Image segmentation based on standard fuzzy *c*-means with bias field is proposed in this paper. The algorithm selected the initial centroid by using *dist-max* initialization method. To determine the practical applicability of the proposed MRFCM-wBE, this paper implemented it. For comparing the results of the proposed method, the algorithms SFCM, IFS, BCFCM and GKFCM with spatial bias correction were used to execute the results from real MRI brain images. In MRFCM iterations are reduced and we get more accurate values. It has proved that the proposed method is robust in clustering it into borders between tissues respectively. Further, the clustering validity using the silhouette method has shown that our proposed method MRFCM-wBE is achieved highest silhouette value in clustering the real brain MRI images [22-25]. The whole experimental results indicate that the proposed algorithmn is more robust to the noises and faster than many other segmentation algorithms.

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