Detection of Brain Tumor from MRI of Brain Using Fuzzy C-mean (FCM)

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Abstract— **The performance of level set segmentation is subjected to appropriate initialization and optimal configuration of controlling parameters which require substantial manual invention. A fuzzy level set algorithm is proposed in this paper to facilitate medical image segmentation. It is directly evolve from initial segmentation by spatial fuzzy clustering. The controlling parameter of level set evolution also estimated from result of fuzzy clustering mean. A fuzzy set algorithm is enhanced with locally regularized evolution. A such improvement facilitate level set manipulation and lead to more robust segmentation. Performance of evaluation of the proposed algorithm was carried on medical images segmentation**

Index Terms— introduction, clustering, Fuzzy clustering, image segmentation, Fuzzy C-Mean, result

1. INTRODUCTION

Intensity inhomogeneity often exists in magnetic resonance imaging (MRI) images due to the imperfection of imaging devices. Intensity inhomogeneity can be generally modeled as a smooth and spatially varying field, multiplied by the constant true signal of the same tissue in the measured image. The spatially varying field is also named as the bias field. A Bias correction is a procedure to estimate the bias field and restore the true signals, thereby eliminating the side effect of the intensity inhomogeneity [2][3]. Among the various bias correction methods, those based on segmentation are most attractive. Parametric model is based on the maximum-likelihood (ML) or maximum a posterior. The (MAP) probability is often used to unify segmentation and bias correction [2], whose parameters can be estimated by the expectation maximization (EM) algorithm [3][4].Such algorithms are sensitive to the initialization of the variables [1][3], which limits their applications in automatic segmentation.

In this paper, first we define a maximum likelihood objective function for each point in a transformed domain, where the distribution overlap between different tissues can be suppressed to some extent, and then energy functional is defined by integrating the maximum likelihood function over the entire image domain. Then we incorporate this energy functional into a multiphase level set formulation. The segmentation and bias correction are obtained via a level set evolution process. The advantage of our method is that the smoothness of the computed bias field is ensured by the normalized convolution [5] without extra cost. The evolution is less sensitive to the initialization, thus well suited for automatic applications.

This paper is deals with MRI fuzzy segmentation of medical image which is more complex due to intrinsic nature of images for detecting tumor, edema there is a need of segmentation and MRI is an important imaging technique for detecting abnormal changes in tissues and organismic images possess good contrast resolution for different tissues and has advantages over tomography and CT .A clustering is

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the most popular segmentation method with FCM. The FCM was shown superior on normal brains and worse on abnormal brain with tumor, edema and the greatest shortcoming over FCM is its oversensitivity to noise. It is intensity based clustering algorithm which is not robust to noisy image. The FCM deals with MR images corrupted by in homogeneities.

2. OBJECTIVE OF THE PRESENT WORK:

2.1Collection of MR image data for processing

- A Liver MR images
- A Brain MR images

2.2Bias estimation and correction using fuzzy c mean of MR images

segmentation of (clusters) an image in object classes and estimates the slow varying illumination artifact(bias field).The Modified Fuzzy C-Means Algorithm for Bias Field estimation and correction of MRI Data.

2.3 MR image segmentation using fuzzy c mean for tumor detection

The performance of level set segmentation by spatial fuzzy clustering

i. The input grayscale image
ii. The result of spatial fuzzy clustering
iii. Modulating argument
iv. The result level set function
v. Historic records of level set evolution

2.4 Work Plan and Methodology:

1. Design of the bias correction function which will perform following function:

2D input image greyscale or color, of type double and Class prototypes. A vector with approximations of the grayscale means of all the image classes. It is also possible to set the values further away from the mean to allow better class separation. With a struct with options

Options. epsilon : The function stops if the difference between class means of two iterations is smaller than epsilon

Options. alpha : Scales the effect of the neighbours , must be large if it is a noisy image, default 1.

Options.maxit : Maximum number of the function itterations

Options.sigma : Sigma of Gaussian smoothing of bias field (slow varying non uniform illumination in CT or MRI scan).

Options.p : Norm constant FCM objective function, must be the larger than one defaults to 2.

2. Design of fuzzy c mean segmentation function

Template radius for spatial filtering and the spatial filter weight with fuzzy thresholding and epsilon value which is Dirac regulator. Adaptive definition of the penalizing item area of the initial contour by giving peripherium of initial contour. We have to give the Coefficient of the internal (penalizing) energy term P(\phi); The product time step*mu must be less than 0.25 for the stability

MR image provide details information about human anatomical structure and tissues. Also MR image is safe compare to CT scan and X- Ray Image. It is not affect the human body. MR Image is providing information for use of further treatment and research area. Fig.2 shows the brain MRI image with the information about different tissues [6].

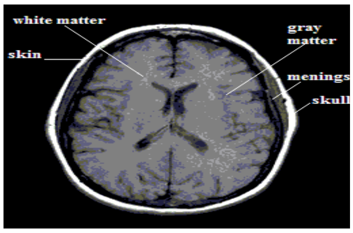

Fig.2: Brain MR Image [7]

3. SEGMENTATION METHODS

Now a days, image segmentation is important role in medical image segmentations. The image segmentation of brain tumor from magnetic resonance images is an important task. The image segmentation is one of the techniques for finding tumor from the MRI. It is time consuming but also generates errors. The image Segmentation by expert is variable [8]. Segmentation takes at least three hours to complete. Several automated technique have been developed for MRI image segmentation. In this paper several automated image segmentation techniques are discussed below:

3.1 Thresholding

Threshloding is one of the simple image segmentation technique. It is process of separating the pixels in different

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classes depending on their pixels gray levels. A thresholding method determines the intensity value, called threshold, which separate the desired classes. Segmentation is achieved by taking threshold value. Based on threshold value, the pixels are grouping with intensity greater than the threshold into one class and remain pixels grouping into another class. The main disadvantage is the simplest form only two classes are generated and it cannot be applied to multichannel images. In thresholding technique, image having only two values black and white. The MR image contains 0 to 255 grey values. Hence, the thresholding of MR images ignores the tumor cells [9].

3.2 Region growing

It is a region based image segmentation method. This process is first requirement of manually select the seed points. Selection of the seed points is based on user criteria. It is also an iteration based method, like clustering algorithms. The algorithm steps for region growing technique are describe below: [10]

1 .In the first step manually select the seed points.

2. In next steps pixels in the region of seeds are examined and it is added to the region accordance with the homogeneity criteria. This process is continued until all the pixels belong to some region.

3. In last step the object illustration is done by growing the regions of pixels. The region growing technique is applied in medical image segmentation. In medical field, it can be applied in kidney segmentation, extraction of brain surface and cardiac images. The main disadvantage of this method is, it requires the user interface for selection of seed the points.[11] Thus for each region that selection of the seed is requires the user interface and very time consuming process.

3.3 Mean shift

Mean shift is a non-parametric clustering technique. Mainly it is used for clustering analysis in computer vision and image processing. Mean shift algorithm is used for clusters an n-dimensional data set. Firstly defining spherical window of radius r in data points and calculate mean of points which located within the window. That means, each and every points algorithm computes its peak. Secondly, the spherical window is move to the means and repeats until convergence. At each iteration , the spherical window will move the portion of data set until maximum peak is reached.

3.4 Clustering techniques

Clustering is the process of collection of objects which are similar between them and are dissimilar objects belong to the other clusters. The clustering is suitable in biomedical image segmentation when the number of cluster is known for particular clustering of human anatomy.

Clustering algorithm are classified two types:

- Exclusive clustering
- Overlapping clustering

In the exclusive clustering, one data (pixel) is belong to the one cluster then it could not belong to another cluster. K-mean is the example of exclusive clustering algorithm. In overlapping clustering, one data (pixel) is belong to the two or more clusters. Fuzzy C-mean is example of the overlapping clustering algorithm. [12]

4. K-MEANS CLUSTERING

K-mean clustering is unsupervised algorithms that solve clustering problem. The procedure for k mean clustering algorithm is the simple and easy way to segment the image using basic knowledge of the clustering value. In k-mean clustering initially randomly define k centroids. Selection of this k centroid is placed in the cunning way because different location makes the different clustering. So that, the better is to place centroid value will be as much as far away from the each other. Secondly calculate the distance between each pixel to selected cluster centroid. Each pixel compares with the k clusters centroids and finding the distance using the distance formula. If pixel has the shortest distance among all , than it is move to particular cluster. Repeat this process until all pixel compare to the cluster centroids. The process continues until some convergence criteria are the met [12]

5. FUZZY C-MEANS CLUSTERING

Fuzzy C-means clustering is the overlapping clustering technique. One pixel value depending upon the two or more clusters centers. It is also known as soft clustering method.

ISSN: 2278 – 7798

Most widely used the fuzzy clustering algorithms is the Fuzzy C-means (FCM) algorithm (Bezdek 1981). The FCM algorithm is the partition of the n element X={x1,...,xn} into a collection of the c fuzzy clustering with respect to the below given criteria.[12][13]

It is based on the minimization of the following objective function:

$$J=\sum_{i=1}^{N} \sum_{j=1}^{c} u_{ij}^{m} |x_i - y_i|^2$$

Where,

m = level of the fuzziness and real number greater than 1.

uij= degree of the membership of xi in the cluster cj

x = data value

Fuzzy C-means is the popular method for medical image segmentation but only consider the image intensity thereby producing unsatisfactory results in noisy images. A bunch of the algorithms are proposed to make the FCM robust against noise and in homogeneity but it's still not perfect. In 2012, J. Selvakumar, A, Lakshmi and T. Arivoli [9] proposed a technique for brain tumor segmentation using the k-means and the fuzzy c-means algorithm. Its use the preprocessing step for filtering the noise and other artefacts in image and apply the K-means and fuzzy c-mean algorithm. This purposed algorithm, fuzzy c-mean is slower than the K-means in efficiency but gives the accurate prediction of tumor cells which are not predicted by the K-means algorithm.

5.1 K-Means Based Fuzzy C-Mean Clustering

It is well known that the output of the K-Means algorithm depends on the initial seeds number as well as the final clusters number. Therefore to avoid such obstacle K-Means based FCM clustering is suggested. The idea behind this suggestion is to supply K-Means with well defined clusters centers based on the optimal calculation instead of random ones. In addition to that it is well known that the fuzzy C-Mean algorithm assign probability for each point to be classified rather than the deterministic class assignment by K-means; therefore one can switch form probability to deterministic by this algorithm.

6. BILATERAL FILTERS

In this work the bilateral filter that introduced by the Manduchi *et al*. (1998) **[14]**, has been adopted. It performs the nonlinear smoothing on image to reduce the noise and retaining the edge information. Nonlinear smoothing is performed by combining the geometric and intensity similarity of the pixels. The filtering operation is given by**[14]**

$$I_b(x,y) = \frac{\sum_{n=-N}^{N}\sum_{m=-N}^{N} W(x,y,n,m)\ I_g(x-n,y-m)}{\sum_{n=-N}^{N}\sum_{m=-N}^{N} W(x,y,n,m)}$$

If *Ig(x , y)* be the grayscale image having values in the range [0, 1] , *Ib(x, y)* will be the bilateral filtered version of *Ig(x, y)*. This equation is simply the normalized weighted average of a neighborhood of *(2N + 1) by (2N + 1)* pixels around the pixel location *(x, y)*. The weight *W(x, y, n, m)* is computed by multiplying the following two factors **[14]**:

$$W(x,y,n,m) = W_S(x,y,n,m) \times W_r(x,y,n,m)$$

Where: *Ws (x, y, n, m)* is geometric weight factor. It is based on the Euclidean distance between center pixel *(x, y)* and the *(x − n, y − m)* pixel as **[14]**:

$$W_S(x,y,n,m) \quad = \exp[\frac{(x-n)^2+(y-m)^2}{2\sigma_z^2}]$$

The second weight *Wr(x, y, n, m)* is based on grayscale intensity distance between the values at *(x, y)* and *(x − n, y − m)*. Again , it is based on Euclidean distance between intensity values as **[14]** :

$$W_r(x,y,n,m) = \exp[-\frac{(I_g(x,y)-I_g(x-n,y-m))^2}{2\sigma_r^2}]$$

For discarding noise terms without disturbing object boundaries, the *Ib* function should be normalized by the W(x, y, n, m).

7. MORPHOLOGICAL OPERATIONS

Morphological operators have been used in the field of the image processing and are known for their robust performance in preserving the shape of a signal, while suppressing the noise. Image morphology provides the way to incorporate neighborhood and distance information into

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algorithms. The basic idea in mathematical morphology is to convolve an image with a given mask (known as the structuring element) and to binaries the result of the convolution using the given function. Choice of the convolution mask and binarization function depends on the particular morphological operator being used. Shrinking or expanding a binary image based on the iterative neighborhood transformations or a"mathematical morphology" as applied by *G. Matheron and J. Serra* **[15]** allows the processing of an image based on its shape. Morphological operations may be viewed as the shape filters which remove information from an image based on the shape of objects in the image, and how they relate to the shape of the filter retaining only the information of interest in the image. There are two basic morphological operators: ***erosion*** and ***dilation***, opening and closing are two derived operations in terms of the erosion and dilation **[16]**.

8. BRAIN MR IMAGES

MRI is a advanced medical imaging technique providing rich information about the human soft tissue anatomy. It has a several advantages over the other imaging techniques enabling it to provide 3-dimensional data with high contrast between soft tissues. However, the amount of the data is far too much for manual analysis/interpretation, and this has been one of the biggest obstacles in the effective use of MRI. For this reason, automatic or semi-automatic techniques of the computer-aided image analysis are necessary. Segmentation of MR images into different tissue classes, especially gray matter (GM), white matter (WM) and cerebrospinal fluid (CSF), is an important task. Brain MR images have the number of features, especially the following: Firstly, they are statistically simple; MR Images are theoretically piecewise constant with a small number of classes. Secondly, they have relatively high contrast between the different tissues. The contrast between MR image depends upon the way the image is acquired. By altering the radio frequency and gradient pulses and by carefully choosing relaxation timing, it is possible to highlight different component in the object being imaged and produce high contrast images. These two features are facilitate segmentation.

8.1 Weighting

MR images can be acquired using the different techniques. The resulting images highlight different properties of depicted materials. The most common weightings are T1 and T2, which highlight the properties of T1-relaxation and T2-relaxation respectively. Selection of most appropriate weighting is important for a successful segmentation. According to the Pham *et al.* the properties of the tissues that are to be segmented have to be known to make a well-founded decision [17].

T1-weighted Images

T1-images shows high contrast between tissues having different T1-relaxation times. Tissues with long T1-relaxation time emit little signal and thus they will be dark in resulting image. In T1-images air, bone and CSF have low intensity, gray matter is dark gray, white matter is light gray, and adipose tissue has the high intensity. T1-images have the high contrast between the white matter and gray matter.

T2-weighted Images

In T2-images, white matter and gray matter are gray and have the similar intensities. CSF is a bright, while bone, air, and fat appear dark. As opposed to the T1-images, T2-images have high contrast between the CSF and bone. The contrast between the white matter and gray matter is not as good as in T1-images.

Spin Density

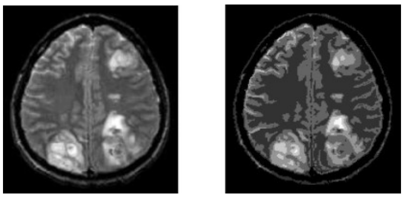
Spin density or Photon Density (PD) is most like Computed Tomography (CT) of all the MR contrast parameters. The spin density is simply the number of spins in sample that can be detected. The observed spin density in medical imaging is always less than actual spin density due to the fact that many spins are bound and lose signal before they can be observed.

8.2 Artifacts

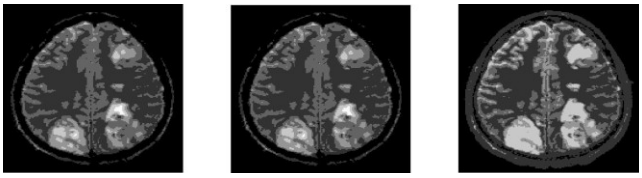
A variety of the artifacts may appear in MR images. Since artifacts change the appearance of the image they may also

ISSN: 2278 – 7798

affect the performance of a segmentation algorithm. The most important artifacts in image segmentation are intensity in-homogeneities and partial volume effect.



(a) (b)



(c) (d) (e)

Figure1: Unsupervised image segmentation of Sarcoma diseased Brain MR image of size (175 × 215) (a) Real image with 3 % of noise (b) Ground Truth (c)-(d) segmented image using HMRF-FCEM framework with histogram based initial parameters and arbitrary initial parameters (e) segmented image using HMRF-EM-SA framework

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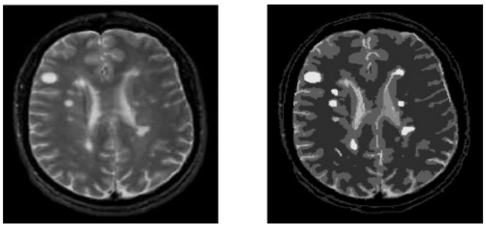
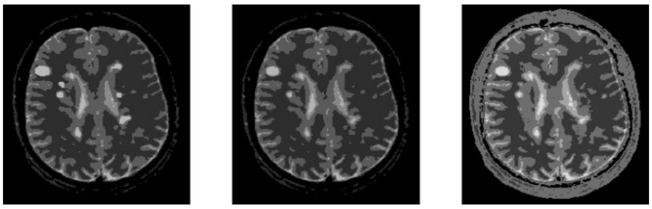
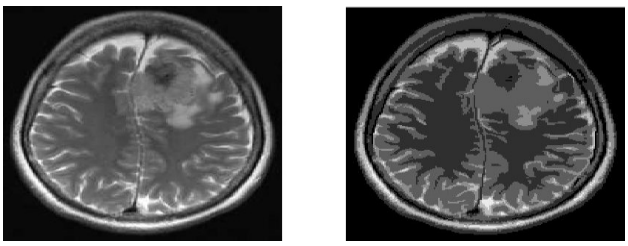


(a) (b)

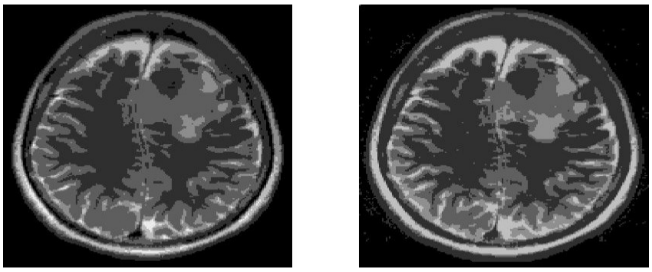


(c) (d) (e)

Figure 2:: Unsupervised image segmentation of Multiple sclerosis from a Brain MR image of size (175 ×215) (a) Real image with 3 % of noise (b) Ground Truth (c) and (d) segmented image using HMRF-FCEM framework with histogram based initial parameters and arbitrary initial parameters (e) segmented image using HMRF-EM-SA framework

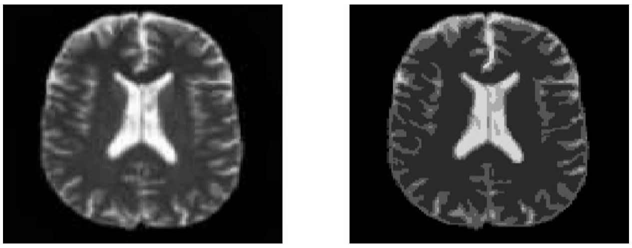


(a) (b)

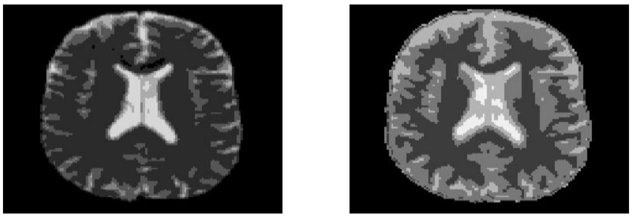


(c) (d)

Figure 3: Unsupervised image segmentation of tumor from a Brain MR image of size (175 ×215) (a) Real image with 3 % of noise (b) Ground Truth (c) segmented image using HMRF-FCEM framework (d) segmented image using HMRF-EM-SA framework

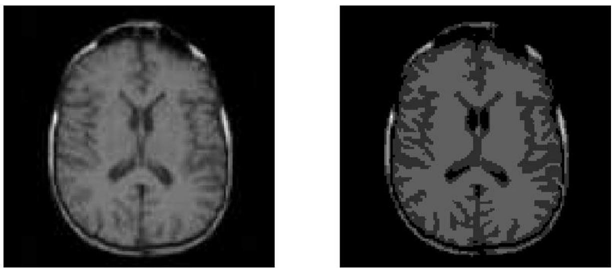


(a) (b)



(a) (b)

Figure 4: Unsupervised image segmentation of diseased Brain MR image of size (128 × 128) (a) Original image with 3 % of noise (b) Ground Truth (c) segmented image using HMRF-FCEM framework (d) segmented image using HMRF-EM-SA framework



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(A) (B)

(C) (D)

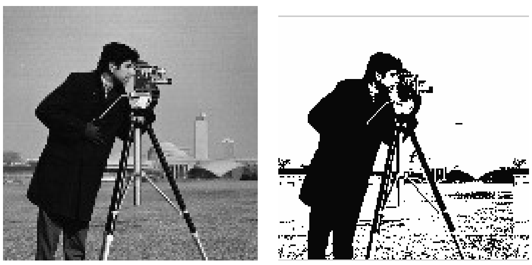
Figure 5:: Unsupervised image segmentation of Brain MR image of size (128 × 128) (a) Original image with 3 % of noise (b) Ground Truth (c) segmented image using HMRF-FCEM framework (d)segmented image using HMRF-EM-SA framework.

9. EXPERIMENTAL RESULT

The proposed algorithm and Fuzzy C-Means algorithm is implemented using MATLAB software and tested on the brain MRI images to explore the segmentation accuracy of the proposed approach. The comparison is made between the Fuzzy C-Means and proposed algorithm. The quality of the segmentation of the proposed algorithm can be calculated by segmentation accuracy which is given as.

$$SA = \frac{\text{(number of correctly classified pixels)}}{\text{(Total number of pixels)}} * 100$$

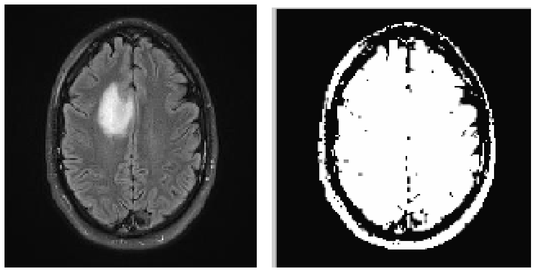
The input image and the corresponding segmented image is shown below.



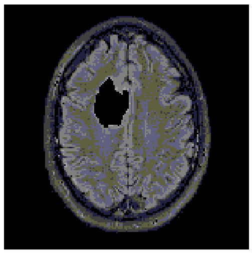
(a) (b)

(c)

Fig.6. Segmentation results of Cameraman image (a) Original image (b) FCM segmentation result (c) Segmentation result by proposed approach with Segmentation accuracy 0.78.



(a) (b)



(c)

Fig.7. Segmentation results of original brain MRI image. (a) Original brain MRI image with tumor.(b) FCM segmentation result (c) Segmentation result of proposed approach with segmentation accuracy 0.64.

10. CONCLUSION

Image processing is the important role in today's world. Now a days, the applications of the image processing can be found in the areas like electronics, remote sensing, bio-medical etc. If we focus the bio-medical applications, image processing is widely used for the diagnosis of different tissues purpose. By use of appropriate image segmentation method and the use of accurate input image is very important technique. In this paper various image segmentation methods for brain MR image have been discussed.

11. FUTURE SCOPE

Future research in the segmentation of the medical images will strive towards improving the accuracy, precision and computational speed of segmentation methods, as well as reducing the amount of manual interaction. Computational efficiency will be particularly important in the real time processing applications.

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Possibly the most important question surrounding the use of an image segmentation is its application in clinical settings. Computerized segmentation methods have already demonstrated their utility in research applications and are now increasingly in use for computer aided diagnosis and the radiotherapy planning. It is unlikely that automated image segmentation methods will ever replace physicians but they will likely become crucial elements of the medical image analysis. Segmentation methods will be particularly valuable in areas such as computer integrated surgery, where visualization of anatomy is a critical component.

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