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A Comparative Study on Medical Image Segmentation Methods

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Abstract
Image segmentation plays an important role in medical images. It has been a relevant research area in computer vision and image analysis. Many segmentation algorithms have been proposed for medical images. This paper makes a review on segmentation methods for medical images. In this survey, segmentation methods are divided into five categories: region based, boundary based, model based, hybrid based and atlas based. The five different categories with their principle ideas, advantages and disadvantages in segmenting different medical images are discussed.

Keywords: Medical images; Image segmentation; Deformable models; Brain image; Retinal image; Cardiac image

Introduction

Image segmentation is the process of partitioning an image into regions or classes that are similar with respect to one or more characteristics [1,2,3]. Automated image segmentation is a fundamental problem in computer vision and medical image analysis. Medical image segmentation provides noninvasive information about human body structure that helps radiologist in surgery planning, treatment planning, surgery simulations, study of anatomical structure, localization of pathology [4-9] etc. MRI (Magnetic Resonance Imaging), CT (Computed Tomography), PET (Positron Emission Tomography), Digital mammography and other imaging modalities are used to produce the medical image. Based on the imaging modalities and other factors the methods for performing segmentation differ [10-12]. Figure 1 shows the different categories of image segmentation.

The remaining part of this paper is organized as follows: Section 2 describes the various segmentation methods, segmentation methods suitable for various medical images is presented in section 3, section 4 provides comparision of various medical image segmentation methods, followed by a conclusion in section 5.

Medical Image Segmentation Methods

Medical image segmentation methods are categorized into Region Based, Boundary Based, model based, hybrid based and atlas based as shown in Figure 1. Region based methods are based on similarities between regions, boundary based methods are based on differences between regions, hybrid methods use both region and boundary image features and atlas based methods are based on image registration between an atlas and the image to be segmented [13].

Region Based Methods

The region based segmentation [2] is partitioning of an image into similar areas of connected pixels through the application of homogeneity criteria among set of pixels. Each pixel in a region is similar with respect to some characteristics.

Let the region R be defined as a predicate function *P*, as

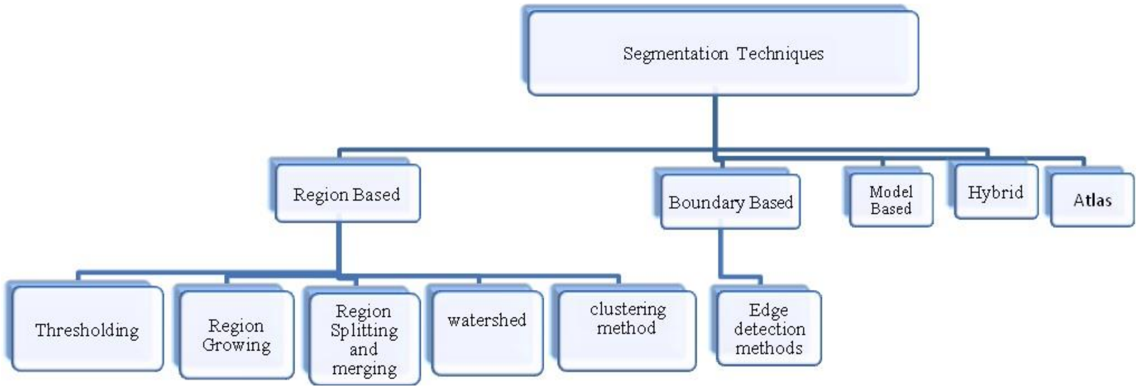


Figure 1. Different Categories of Medical Image Segmentation

$$P(R_i) = true, i = 1,\dots,K \quad (1)$$

The partition of an image Ω into *K* disjoint regions satisfies

$$\Omega = \bigcup R \quad (2)$$

$$R_i \cap R_j = \{\ \}, i \neq j \quad (3)$$

$$P(R_i \cup R_j) = false, i \neq j \quad (4)$$

Region based methods are categorized into: thresholding, region growing, region splitting and merging, watershed and classification.

In thresholding [14], based on a threshold value T the pixels in the image are grouped.
Thresholding for an image f(x, y) is defined as

$$f(x,y)= 1 \text{ if } f(x.y) \geq T$$

$$f(x,y)= 0, \text{ if} f(x,y) < T \quad (5)$$

Based on image histogram and local properties many thresholding methods have been developed [3,14]. Thresholding can be global are or local. If only one threshold is selected for the whole image, then it is global thresholding. In local thresholding, the whole image is divided into many sub images and different threshold value is assigned to each sub image.

Different methods are used to select threshold. One method is manual selection, which is based on trial and error method. Second method is based on mean or median and histogram. Third method is unimodal threshold selection algorithm which does not require much specific knowledge of image. Unimodal threshold selection algorithm is used in medical images.

Thresholding is obtained by comparing individual pixels in an image with threshold value T.If pixel value is below threshold value then it is set to the background value, otherwise it assumes foreground value.

Automatic thresholding is done using an iterative thresholding scheme:

i. Select a threshold value T
ii. Compare individual pixels in an image with threshold value T and assign '0' for one set of pixels and '1' for other set of pixels based on equation.
iii. Find mean intensity M1 and M2 for the pixels in two sets.
iv. Find new threshold T=1/2(M1+M2)
v. Repeat the above steps till the value of T converges

Limitation in automatic thresholding is time complexity increases with size of image, since mean is calculated at every iteration. Otsu's method is used to overcome the above limitation. In this method, optimal threshold is identified using histogram of image.

Region Growing or region merging [2] is a classical segmentation technique. In this method, segmentation is started with seeds that belong to the image of interest. Each seed represent a region. The region grows by connecting the neighboring pixels based on the homogeneity criterion. Region growing can be seeded or unseeded. In seeded region growing, seed is selected manually.

Algorithm: Region growin:

i. Select seed pixels
ii. Select similarity criteria
iii. Grow regions by combining seed pixels with the neighboring pixels that satisfy similarity criterion
iv. Stop region growing when no more pixels met similarity criterion

Many seed growing methods are available in literature and these methods are differentiated by the definition of homogeneity criteria. Adam and Bischof [15] defined a predicate in (6) with threshold T

$$P(x,r) = |f(x)-\mu_r| < T \quad (6)$$

where T is a threshold. Adams region growing examines growing multiple disjoint regions. Unseeded region growing is proposed in [16]. In this unseeded region growing, there is no need for region seed point initialization. Hijjatoleslami and Kitter [17] introduced a contrast based region growing approach. This method is based on assumption that region which is to be segmented would appears as a bright or dark object relative to the surrounding. This assumption is not valid for all applications. Udupa and Samarasekera [18] introduced region growing approach based on fuzzy connectivity technique. This method is based on the path of strongest affinity between each point and seed point. This method is used for various medical applications. In [19] a region growing approach is proposed by using both regions growing [17] and fuzzy connectivity region growing [18] which is used in segmentation of pulmonary nodules in thoracic CT scans.

The region growing method generates connected region and this method can correctly segment the regions having same properties and are spatially separated .In region growing, different starting points may not grow into similar regions and also if the homogeneity criterion is not properly selected the regions spread or merge with adjacent regions [2].

The region which does not satisfy homogeneity criteria can be subdivided using region merging technique [20]. Combination of region splitting and region merging is known as region splitting and merging. Split and merge image segmentation techniques are based on a quad tree data representation. In this, a square image is splitted into four quadrants if the original image segment is non-uniform in attribute. If four neighboring squares are found to be uniform, they are merged into single square composed of the four adjacent squares. Region splitting and merging can be processed with the following steps:

i. a) Split the entire image region R into four sub regions if it does not meet some homogeneity criteria
   b) Merge the sub regions of the parent node that meet the homogeneity criteria
   c) If no splitting and merging possible then returns
ii. For each sub region R_i split and merge the regions

iii. If region splitting and merging is completed for whole image, check adjacent regions in the quadtree across parent nodes and repeat the previous steps.

These methods are less sensitive to image noise than thresholding methods due to the use of regional properties.

Watershed Algorithm is commonly used for many medical imaging applications. Watershed Algorithm uses image morphology [1]. In this algorithm atleast one marker is selected interior to each object of the image including the background as a separate object. An operator can select the markers or by using an automatic process the markers can be selected. After marking, the objects can be grown by a morphological watershed transformation [21]. The disadvantages of Watershed Algorithm are over segmentation, under segmentation and sensitivity to noise. In [22] watershed transform and atlas registration are combined and used in knee cartilage segmentation and gray matter/white matter segmentation in MR images [23].

Clustering means grouping set of objects into classes of same characteristics. In clustering similarity is determined by distance measure such as Euclidean distance or Mahalanobis distance [24]. For K number of clusters and N number of data points, the matrix

$$U_{KXN} = [\, U_{Ki}],\ K=1, 2,\dots,k \quad \text{and} \quad i=1,2,\dots,N \tag{7}$$

represents the partitions of data set, where U_{Ki} represents the membership of data point x_i in cluster C_K.

The centroid of cluster C_K is

$$V_k = \Sigma\, U_{Ki}\, x_i \,/\, \Sigma\, U_{Ki}\ ,K=1, 2,\dots,k \tag{8}$$

K means clustering, fuzzy C means clustering and Expectation Maximization are commonly used unsupervised clustering methods.

K Means (KM) [25] or hard C means was first proposed by Forgy and Macqueen. In KM algorithm, data which is in one cluster could not be included in another cluster [24].
The membership value U_{Ki} must satisfy

$$U_{Ki} = \ \forall k,\forall i,\ U_{Ki} = \{0, 1\},\ \forall i,\ \Sigma\, U_{Ki} = 1 \text{ and } \forall k\ ,0< \Sigma\, U_{Ki} < N \tag{9}$$

K Means clustering algorithm is given below:

i. Choose 'K' number of clusters
ii. Choose a set of 'K' points as center of clusters
iii. Assign remaining points to their closest cluster center for each cluster
iv. Calculate a new cluster center for each cluster
v. Repeat the above two steps until cluster center do not change

K Means clustering model quickly converges. It is sensitive to noise, so if it fails to converge then lot of misclassifications occur.

Fuzzy C means [25] is a soft segmentation algorithm. It was developed by Dann in 1973 and improved by Bezdek in 1981. It is a generalization of K means. It allows overlapping of data with two or more clusters at different degrees of memberships.

Algorithm: Fuzzy C means algorithm

i. Initialize membership matrix $U = [U_{ij}]$,where U_{ij} is the degree of membership of measured data X_i in the cluster j
ii. Calculate center vector C_i with U_{ij} at Kth iteration

$$C_i = \frac{\sum_{j=1}^{n} U_{ij}^{m} x_i}{\sum_{j=1}^{n} U_{ij}^{m}} \tag{10}$$

iii. Update membership matrix U for Kth step and (K+1)th step

$$U_{ij} = \frac{1}{\sum_{K=1}^{C} \left(\frac{d_{ij}}{d_{kj}} \right)^{\frac{2}{m-1}}} \tag{11}$$

where $d_{ij} = x_j - C_j$

iv. If $\|U(K+1) - U(K)\| < \epsilon$, then stop; otherwise return to step ii.

Mashor [26] proposed a modified version of K means known as Moving K means (MKM) clustering. This MKM clustering can overcome problems in clustering such as dead centre and redundancy. Siti and Nor Ashidi [27] proposed Adaptive Fuzzy K means clustering algorithm. This algorithm uses an adaptive, iterative fuzzy and belongingness concept to obtain the optimum value of clusters centre. In [28] possiblistic C-means approach is proposed for clustering. This approach does not use the probabilistic constrain but stores the compatibility of elements with different classes. Noise can be efficiently eliminated, but this form of clustering frequently comes with coincident prototype [29] due to excessive independency of cluster prototypes. In [30] possiblistic fuzzy c means algorithm is proposed to overcome this problem by mixing fuzzy c means with hard c means. In [31] hybrid c means clustering model is proposed for MR brain image segmentation. This method accurately and efficiently segments the MR images in the presence of intensity non-uniformity.Expectation Maximization (EM) algorithm [32, 33] is an iterative clustering algorithm which has greater sensitivity to initialization than above mentioned clustering methods [34]. EM algorithm follows the same clustering principle of K means and FCM with an assumption that the data follows Gaussian Mixture model [13]. Clustering algorithms are computationally fast, but do not directly incorporate spatial modeling and therefore sensitive to noise and intensity inhomogeneities.

Edge Based Methods

Edge or boundary based methods are based on detecting edges or pixels between different regions. The edge based methods are computationally fast and they do not need a priori information about image content. An edge or boundary on an image is defined by the local pixel intensity gradient [2].Two main edge based segmentation methods are histogram technique and gradient based method. In histogram technique, histogram is calculated from entire pixel in the image based upon color or intensity and then edges and valleys in image.A gradient is an approximation of the first order derivative of image function. Most of the edge detection methods use gradient operators. Laplacian operators can also be used for edge detection. Many edge detection algorithms have been proposed such as Roberts, Sobel, Prewitt, Laplacian and Canny which are based on the difference of gray levels [39],[40]. Laplacian or gradient based methods are sensitive to noise.Edge based method work well only on images with good contrast between different regions. Disadvantages are it detect all edges, hence, it is very difficult to find relation between edges and region of interest and is sensitive to noise.

Model Based Methods

Image segmentation remains challenging, due to the presence of cluttered objects, object texture, image noise, variations in illumination and various other conditions in image. Segmenting structures in medical images are difficult because of the complexity and variability of the anatomic shapes of interest. Sampling artifacts, spatial aliasing and noise can cause the boundaries of images indifferentiate and disconnected. To address these difficulties, model based methods have been used with considerable success, because of their ability to integrate high-level knowledge with information from low-level image processing. Model based methods can be either region based or boundary based.

Most common model based methods are deformable models and statistical shape and appearance models [41-43].Deformable Models [44, 45, 46] are curves or shapes that deform under the influence of some external or internal force. Deformable Models are able to accommodate the variability of anatomical shapes over time. Compared to local edge based methods, deformable models have the advantage of estimating the boundaries with smooth curves or surfaces which can bridge boundary gaps. Deformable Models are classified as parametric deformable models and Non- parametric deformable models.Parametric deformable models or active contour models or explicit model or snakes [44] is an energy minimizing model. Snakes are computer generated curves that move within the image to find object boundaries under the influence of internal and external forces. Active contours transforms a segmentation problem into a partial differential equation (PDE). The procedure for active contour model is:

i. Snake is placed near the contour of Region of Interest (ROI).
ii. An energy function consisting of internal and external forces are constructed. The internal forces are responsible for smoothness while external forces guide the contours towards contour of ROI.
iii. Snake is attracted towards the target with the internal and external forces within image. These forces control the shape and location of snake within image.

Snakes are represented as,

$$C(s) = (x(s), y(s)),\ 0 \leq s \leq 1 \tag{12}$$

With the influence of internal energy E_{in} (due to contour bending) and external energy E_{ex} (due to image data and external constraints), the contour shape change can minimize the energy function as,

$$E(C) = \int \left[E_{in}(C(s)) + \lambda E_{ex}(C(s)) \right] ds \tag{13}$$

Here λ is a weighted constant.

Active contour models can overcome speckle induced error and is used in medical image boundary detection. These models are faster than non-parametric deformable models [47], [29].The limitations of this method are small capture range and complexity in moving into concave boundary region [49]. These also require use interaction in determining the curve around detected object. Energy function often converges to minimum local energy, so snake should be usually placed near the boundary of ROI. Xu and prince [50] proposed Gradient Vector Flow (GVF) to overcome the problems. According to this method, the energy function

$$E = \iint \mu\left(u_x^2 + y_x^2 + v_x^2 + v_y^2\right) + \left|\nabla f\right|^2 \left|g - \nabla f\right|^2 dxdy \tag{14}$$

can be minimized with the vector field GVF g= (u, v). In equation (14), μ is blending parameter, u_x, y_x, v_x and v_y are derivatives of the vector field and ∇f is the gradient of the edge map. GVF attains larger capture range, but the capture range cannot be extended to the whole image. Sum and Cheung [51] proposed Boundary Vector Field (BVF) based on interpolation which extends capture range to the entire image but cannot extract acute concavities. In this method, a threshold is applied to generate binary boundary map of input image. In [49] Fluid Vector Flow (FVF) model is proposed which gives better results for capture range than above mentioned methods.FVF is executed in three stages:

i. Binary Boundary Map Generation

For an input image *I(x,y)*

a) Apply a Gaussian smoothing filter to the input image
b) Apply a gradient operator to find edges in the image
c) A threshold T ϵ [0,1] is used to generate binary boundary map

The boundary map is defined as

$$M_B(x, y) = \left|\nabla(-G_\sigma(x, y))\right| * I(x, y) \tag{15}$$

where $G_\sigma(x, y)$ is a Gaussian smoothing filter with standard deviation σ,* is convolution operator and ∇ is gradient operator.

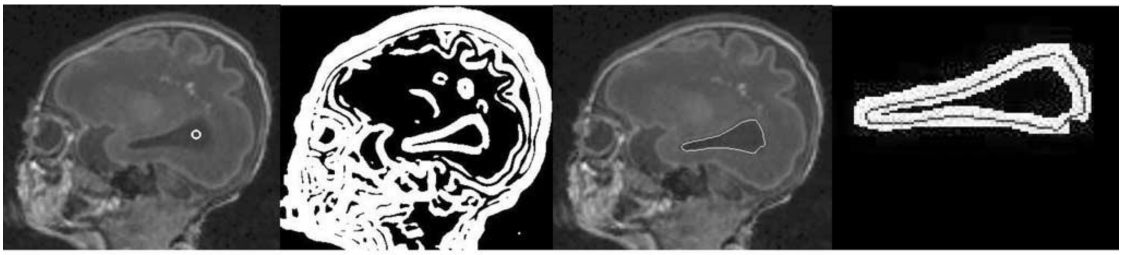
ii. Vector Flow Initialization
   a) Initialize contour to initialize the external force field
   b) Program automatically detects initialization and generate external force field accordingly
   c) Compute internal energy
   Initial forces will push active contour to the neighborhood of target object.

iii. Fluid Vector Flow Initialization
   Automatically selects a control point from object boundary and generates new external force field evolve active contour.

This point flow freely along object boundary like a drop of fluid,update external force field and further evolve active contour until convergence is achieved.Figure 2 shows the results of FVF on head MRI image to extract low intensity brain ventricle region. One of the drawbacks of parametric approach is their inability to split and merge. Split and merge is needed when more than one region of interest is to be detected in an image [52]. Non- Parametric Deformable Model or geometric deformable model [53] was proposed based on level set method and curve convolution theory [54]. Geometric deformable model performs image segmentation by starting with an initial curve and evolving its shape using the speed equation

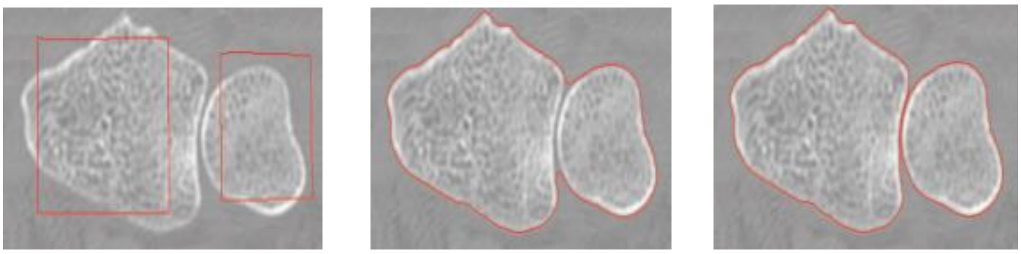
$$\frac{\partial X}{\partial t} = V(c)N \tag{16}$$

where X denotes the curve moving in time t, N is the moving curve's inward normal, c is curvature and $V(c)$ is speed function. During the evolution process curvature deformation and constant deformation are used and the speed of curve evolution depends on image data. The curve evolution stops at object boundaries. This evolution can be performed using level sets.



(a) (b) (c) (d)

Figure 2. FVF process **(a)** Target object with initial contour added **(b)** the binary boundary map **(c)** the final contour of FVF in the image **(d)** a zoomed-in view of the binary boundary map that restricts the final contour inside an envelope.



(a) (b) (c)

Figure 3. Level set segmentation of bone: **(a)** initialization **(b)** standard geometric deformable model **(c)** topology-preserving geometric deformable model.

Level set method was developed by Osher and Sethian. Complex shapes and topological changes can be handled by this method. In this method, a level set function represents the curve with extra dimension of time. The level set function is a higher dimensional function represented as (x, y, t) [45]. Parameterization is not needed in the evolution of curve and surface, therefore this method can automatically handle topology changes. However, topology should be preserved in fixed anatomy. In [55] a topological preservation geometrical model is proposed. In this method at each step of evolution only simple points are allowed to change. Figure 3 shows level set segmentation of bone.

In [45] a term called stopping function is added, which allows the contour to stop on the edges. This model is called Geodesic Active Contour model. The level set function for this with the front curve (zero level set) of evolving level set C is given as

$$E(c) = \int [g(\nabla IC(s))]C(s)ds \tag{17}$$

where $g(\nabla I) = \frac{1}{1+\nabla_{12}}$

The classical stopping function is based on image gradient. In this classical function, the edge stopping term never equals zero and the moving curve may cross the boundaries of object. To overcome these problems alternate stopping functions are proposed [56]. Reference [52] uses logarithmic dependent stopping function for heart chambers segmentation which provides better performance than other stopping functions. Level set method captures multiple objects and complex geometries. This method is slow and edge stopping function depends on image gradient therefore objects with edges defined by gradients can be segmented.Statistical shape and appearance model or Active shape and appearance model (ASM) consists of a statistical shape model known as Point Distribution Model (PDM) [42]. In this model, segmentation is achieved by placing the model on the image and then using least square estimation rotation, translation and scaling parameters are iteratively estimated with a constrain that weight of instance shape should be within suitable limits for similar shapes. In these methods, an a priori model is deformed based on the information from a training set .Active Appearance Model (AAM) can be obtained by extending ASM to gray level modeling [57], which represent the shape and texture variability present in training set. In [58] the application of AAM and ASM to cardiac images is described.

Other Model Based Methods

Bayesian approach considers all quantities as random variables and it uses Bayesian decision theory as a tool of probability. Bayesian methods are based on statistical classification. Markov Random Field (MRF) [35], [36] is a Bayesian approach. It is multidimensional extension of Markov chains.MRF considers image segmentation as labeling problem in which image pixels are labeled. MRF is a statistical model used to model spatial relations that exist in the neighbor of pixels.By using neighborhood information, influence of noise in segmentation is decreased. Baum [37] developed Hidden Markov Model (HMM). In HMM, current state cannot be determined only by relying on current observation. Conditional Random Fields is developed [38] for obtaining better smoothing in the probability fields.

Hybrid Methods

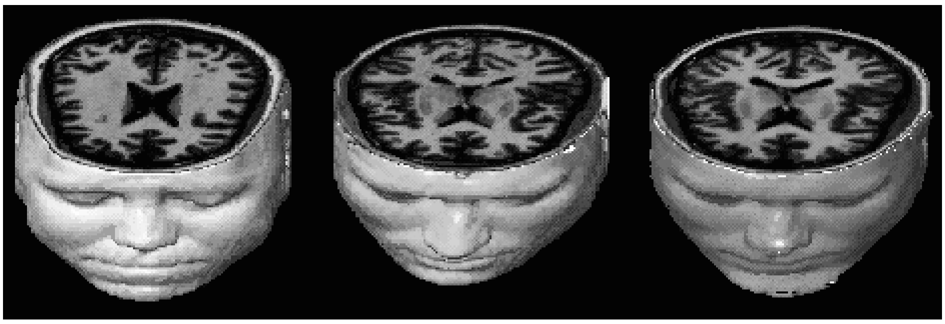
Hybrid Methods use the concept of both region based methods and boundary based methods. Deformable models are sensitive to noise and spurious edges. To address this limitations region constraints can be integrated with boundary based deformable models. Ronfard [59] introduced a region based energy criteria for active contours assuming partition of an image into background and object regions. Geodesic Active region [60] integrates edge and region based modules in a level set framework. Deformable models can be propagated in a probabilistic manner by integrating deformable models with inference methods. In this method, traditional energy minimization is formulated as a maximum a posteriori estimation problem. The drawback of using probabilistic formulation is they use only edge information. The probabilistic active contours are integrated with Markov Random Fields (MRF) [61] to overcome the above mentioned drawback. In [62] deformable model is integrated with Collaborative Conditional Random Fields to segment objects in clutter and region ambiguities accurately. In probabilistic segmentation annotated training data should be defined which limits this scheme. This problem can be avoided by using Expectation Maximization (EM) algorithm. An EM driven geodesic active contour [63] for lymphocyte segmentation was developed. This model is able to solve object overlap by using an edge path algorithm without training data. An energy minimization method based on partitioning of a graph into minimum-cut/maximum-flow graph cuts was proposed in [64] and then modified in [65]. A hybrid method based on graph cut and local vessel models is used for liver vessel segmentation [66]. This method takes the advantages of local modeling such as accuracy and robustness and global optimality advantage of graph cut technique. The PDM is combined with classifier for robust brain extraction [67].

Atlas Guided Approaches

In atlas- based segmentation [68], segmentation of target image is obtained from atlas image (manually labeled image). In this approach, target image is segmented by registration and propagation of N atlases. Atlas can be defined as a pair (I_i , L_i) consisting of an image I_i and a corresponding segmentation or label L_i . Atlas- based segmentation is used as a segmentation tool for medical image segmentation when a standard atlas is available. Atlas based segmentation is processed with the following steps:

i. Finds a one to one transformation that maps an atlas image to the target image. This process is known as atlas warping
ii. Atlas warping results in a correspondence field, which maps each pixel in the atlas space to one in the coordinate system
iii. Spatial priors are applied to correspondence field resulting in patient specific spatial priors, which guide the segmentation

A single atlas or multiple atlases can be used for atlas based segmentation. Reference [69] shows that atlas based segmentation with multiple atlas produces better results than single atlas. Multiple atlas results in high computational cost and shape variance. Atlas based methods are mainly used in MR brain imaging.Atlas warping for a MRI head scan is shown in figure 4:



(a) (b) (c)

Figure 4. Demonstration of atlas warping: **(a)** template image **(b)** target image **(c)** warped template

Existing atlas based methods are generalized as single atlas based segmentation, average shape atlas based segmentation and multi atlas based segmentation with averaging as decision fusion. In [70] atlas based segmentation with single atlas is proposed. In this two different approaches are used. A single best atlas can be selected by visual inspection or based on predefined criteria. Then the selected atlas is registered to obtain segmentation in target image. In Average Shape Atlas based segmentation, from the available N atlases, a single atlas A_i was randomly selected. Then A_i is registered with remaining N-1 atlases. By averaging the deformed atlas the average shape atlas(ASA) was obtained.Target segmentation was completed by registering the single average shape atlas to target image and propagating its segmentation. In Multi-atlas segmentation, instead of single atlas, multiple atlases are registered to a target image. Then segmentation is obtained by propagating labels of atlas images to target image. Atlas guided approach provide a standard system for studying morphometric properties. But due to anatomical variability, even with non-linear registration methods accurate segmentations of complex structures is difficult.

Other Approaches

Mean Shift Method

Mean shift approach is a non-parametric technique for the analysis of a complex multi-modal feature space and identification of feature clusters. Mean shift method avoids estimation of probability density function and consists of two main steps-discontinuity preserving filtering and mean shift clustering. The procedure for mean shift approach:

i. Find a window around each data point
ii. Compute mean of data within the window
iii. Translate density estimation window
iv. Shift the window to the mean and repeat till convergence

Graph Based Image Segmentation

Graph Based approaches play an important role in image segmentation. In this approach a weighted graph G=(V,E) is formed with node set V and arc set E. Graph nodes are called vertices and arcs are called edges. The nodes v ϵ V correspond to image pixels and arcs (v_i, v_j) ϵ E connect the nodes v_i, v_j according to some neighborhood system. Every node and arc $(v_{i,} v_j)$ ϵ E has a cost representing some measure of preference that the corresponding pixels belong to the object of interest.Graph cut solve a region-based segmentation problem by the use of minimum s-t cut/maximum flow combinatorial optimization algorithms. In addition to the set of nodes V, it contains two special terminal nodes, source s and sink t. These terminals are hard-linked with the segmentation seed points and represent the segmentation labels (object, background).The goal of graph cut is to minimize the objective function given in equation (18)

$$C(L) = \lambda R(L) + B(L) \tag{18}$$

where λ is a weighted combination of a regional property term $R(L)$ and a boundary term $B(L)$.

Comparision of various medical image segmentation methods

Table 1. Comparisons of various medical image segmentation methods

Segmentation Approaches	Method Description	Advantages	Disadvantages	Applications
Thresholding	Based on threshold value pixels in the image are grouped	Fast Simple Easy to implement	Distribution of intensity in most of medical images is very complex, in such cases it is difficult to find threshold. Does not consider spatial constraint	Useful for structure that have separated intensity distribution such as outer body, lung and bone [13]
Region Growing	Divide image into	Fast Less sensitive to	Leakage occurs if boundary is blurred	Combined with other methods to produce better

	homogeneous and spatially connected regions	noise than thresholding	Sensitive to start point location	results Commonly used for segmentation of CT images
Watershed	Mathematical morphological approach. It segments image region into catchment basins(low points in intensity)	Always able to produce complete division of image	Over segmentation Sensitive to noise	Combined with atlas registration and used for Knee cartilage segmentation, MRI brain segmentation. Suggested with a preprocessing step,for example mammographic mass detection.
Clustering K means FCM EM	Grouping together pixels having same properties	Perform well with spatial constraints. Prior training not required	Sensitive to noise and inhomogenities Not produce good results in CT images,since the intensity distributions of many organs overlap	Commonly used for MR brain images. Used as starting point for other techniques, such as generating an initial contour for deformable models
Edge Based Method	Rely on boundaries of region	Easy to extract	Edge information is unreliable and often broken	Detect edges in noisy images.For example, prostate in ultrasound images,left ventricles in cardiac MR, aortas in cardiovascular MR and knee joints in CT images.
Deformable Model Parametric Non-Parametric	Curves move within image to find object boundaries under the influence of internal and external force.It transforms segmentation problem into PDE framework	Parametric: Overcome speckle induced error Accurate Inexpensive Fast Non-Parametric: Capture multiple objects and complex boundaries	Parametric: Computational complexity high Capture range limited Unable to extract concave shapes Non-Parametric: Slow Sometimes lack accuracy Edge stopping function depends on image gradient, therefore objects defined by gradients can be segmented	Commonly used in medical images
Atlas Based Approach	Powerful tool when a standard atlas or template is available	When there is not enough contrast between tissues atlas methods produce good results	Time consuming	Well suited for segmentation of structures that are stable over a large population like human brain

Conclusion

Medical image segmentation is a difficult process because of the complex anatomical structures. Moreover the imaging modalities, artifacts, noise and intensity inhomogeneity affects the performance of the segmentation. The various methods for medical image segmentation, their problems and their application to various medical images have been presented. Threshold methods are fastest and simplest when compared to other methods but sensitive to artifacts. Results of threshold method are better for structures having separated intensity distribution such as outer body, lung and bone. Region growing methods are fast, less sensitive to noise but they are not suitable if the boundary is blurred. Clustering methods are suitable for MRI brain segmentation methods. Deformable models are commonly used in medical images. Model based and atlas based methods are not sensitive to noise and leakage but are time consuming. Each method has its own advantages and limitations. In conclusion, no single method can be best suited for all medical images. The method that is more advantageous for one medical image cannot be applicable for another image. Therefore the methods for medical image segmentation should be carefully selected to improve the segmentation accuracy. Future research in medical image segmentation is aimed at improving accuracy, precision and computational speed of segmentation methods.

Conflict of interest: This is a work done by gathering the information present in the literature. This can be used by the reader to know about existing methods in Medical Image segmentations and its future scope. Potential financial and personal relationships have not been obtained from anyone for the submitted manuscript. The authors declare that they have no conflict of interest.

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