IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

A REVIEW ON DIFFERENT METHODS OF IMAGE SEGMENTATION

[1]Joanna S. Mota, [2] Maruska Mascarenhas

[1]Student, [2]Associate Professor

[1]Department of Computer Engineering,

[1]Goa College of Engineering, Goa, India

Abstract: Medical Images play a crucial role in disease diagnosis. Image segmentation is the process by which a digital image is partitioned into multiple segments (sets of pixels). The main purpose of image segmentation is to simplify the representation of an image so that it becomes easier when it comes to further image analysis, visualization, object representation, and other image processing tasks. Any type of image can be used for segmentation such as grayscale, color, motion, etc. Segmentation techniques are basically used to identify objects in an image for object-based measurements such as the size and shape of the object. In this paper, various techniques that are used for image segmentation are discussed and summarized by emphasizing their characteristics, advantages, and disadvantages. The methods discussed in this paper are thresholding methods, clustering methods, watershed segmentation, and edge-based segmentation techniques.

***Index Terms* - Medical Images, Image Processing, Image Segmentation, Thresholding, Clustering Segmentation, Watershed Segmentation, Edge-based Segmentation.**

I. INTRODUCTION

Image segmentation refers to the procedure of segmenting a digital image into N number of parts. The images are portioned on the basis of a set of pixels or pixels in the region that are comparable on the basis of some homogeneity criteria, for example, texture, color, intensity [1]. Image segmentation splits an image f (x, y) into disconnected and nonempty subsets. From these subsets, a larger amount of data can be effectively separated and extracted. Applications of image segmentation include medical image processing, satellite images, entity identification and recognition, criminal analysis, quality assurance in industries, face recognition, etc. Because of the significance of the image segmentation, a vast number of algorithms have been proposed, as the choice of the algorithm absolutely relies on the format of the image and the type of the issues or problems. Image segmentation techniques are based upon two approaches:

1) Discontinuities based: In this class, segmentation of an image is done on the idea of unexpected change in the intensities of the grey level of an image. Here, more attention is given to the identification of lines, edges, and isolated points. For the detection of discontinuities algorithms like edge, detection can be used.

2) Similarities based: Segmentation is done on the basis of similarity in intensities or grey levels of a picture. Our main intention here is to identify similar points, edges, and lines. For detecting similarities algorithms like region-based segmentation methods and thresholding can be used. In this approach, the image is partitioned according to the similarities between the regions and some predefined criteria.

II. METHODS

2.1 THRESHOLDING METHOD

The thresholding method is an image segmentation as well as an image preprocessing technique. It is a really simple method in which a greyscale image is converted to a black and white image. A black and white image is an image that has only black and white coloring.

2.1.1 Global Thresholding

In global thresholding, one single threshold value is used to convert the entire image to a black-white image. It is used when the intensity distribution between the foreground and background objects is very distinct, such that only one value of the threshold is enough to differentiate both the objects apart. Commonly used thresholding methods are the Otsu method, entropy-based thresholding, etc.

2.1.1.1. Otsu thresholding

The main aim of Otsu thresholding is to find the optimal threshold value so that the within-class(intra-class) variance is minimal and the between-class(inter-class) variance is maximal.

1. Compute histogram and probabilities of each intensity level of the image
2. Set up initial class probability and class means
3. Step through all possible thresholds t=1…. maximum intensity
    a. Update class probability and class mean
    b. Compute interclass variance
4. The desired threshold corresponds to the maximum interclass variance

2.1.1.2. Iterative Thresholding (A New Iterative Tri-class Thresholding Technique)

This method is slightly based on Otsu's method. Firstly, Otsu's method is applied to the image and the means of the two classes, and the threshold is selected. Now instead of classifying the image into two classes based on the threshold obtained from otsu's thresholding, this method classifies the image into three classes based on the means of the two classes which are derived. The three classes are obtained as foreground with pixel values greater than the larger mean, the background with pixel values less than the lesser means and the third class contains the pixel values which are between the larger and the smaller mean and it is called "to-be-determined" (TBD). For the next iteration, the previous foreground and background are kept unchanged and otsu's method is applied to the TBD region and again classified into three regions similarly. In the final iteration, the image will be separated into two classes instead of three. The foreground being the union of the foreground of all the iterations, and the background calculated similarly.

2.1.2. Local thresholding

Global thresholding does not provide a good result for all images. For images that do not have a distinct intensity distribution between foreground and background objects cannot be segmented using global thresholding. For medical images, thresholding may provide good results in one part of the image while it may not give satisfactory results in other parts of the image, hence, in order to counter such kinds of problems local thresholding is used. In local thresholding, different threshold values are selected for different parts of the image. To find different threshold values for the same image, the local thresholding algorithm divides the image into different sub-images and the threshold value for each sub-image is calculated. The results of the thresholding are then merged to get the final thresholded image. To find the sub-images, the image is divided by vertical and horizontal lines such that each sub-image contains both background and object. Different methods are used to find the threshold value of each region. Finally, interpolation is needed to produce appropriate results. Local thresholding takes longer than global thresholding to segment the image but it gives good results for images with varying backgrounds.

2.2. Clustering

Clustering techniques segment the image into clusters such that pixels with similar characteristics fall into one cluster. Clustering is a method that divides the data elements into clusters so that the elements in the same cluster have more similarily to the elements in the same cluster than the elements in different clusters. There are basically two types of clustering methods: The hierarchical method and partition-based method. In the hierarchical method, the root of the tree represents the entire database and the internal nodes represent clusters. Whereas, the partition-based methods use optimization methods iteratively to minimize an objective function. In between these methods lie the various algorithms that are used to find clusters [4]. There are two basic types of clusters:

Hard clustering: Hard clustering divides the image into clusters in such a way that one pixel can only belong to exactly one cluster. These are the methods which use membership functions having values either 1 or 0 i.e. one pixel can belong to a certain cluster or no. An example of hard clustering is the k-means clustering technique, in which, the centers are computed, then each pixel is assigned to the nearest center.

Soft clustering: Soft clustering is more natural because in real life exact clustering is not possible due to noise. Hence, soft clustering is more useful for segmentation in which division is not strict. An example of this type of method is Fuzzy C-Means clustering method, in which pixels are classified into clusters by partial membership i.e. a pixel can belong to more than one cluster and this is described by membership values of the pixels.

2.2.1 K-means

K-means algorithm aims to partition N observations into k-clusters so that every observation belongs to the cluster with the nearest mean. K stands for the number of clusters in which the data is to be classified.

Algorithm [5]:

1. Choose n number of clusters to start our clusters.
2. Assign initial clusters by associating every observation with the nearest mean.
3. Reassign feature vectors x_i to clusters such that the centroid of each of the k-clusters becomes the new mean.
4. Steps 2 and 3 are repeated till convergence is obtained.

Sum of squared error (SSE) that define the condition of repeating the loop is given by the equation:

$$SSE=\sum_{j=1}^{k}\sum_{i=1}^{n}\mathrm{dist}(x_i,c_j)^2. \qquad \text{(Eq.1)}$$

The problem is that it is computationally difficult and an unsuitable choice of k can also yield poor and inaccurate results. The advantage of the K-Means clustering algorithm is that the algorithm is fast and simple, and it is highly efficient and scalable for large data sets. And its time complexity is close to linear, hence, it is suitable for mining large-scale data sets. The disadvantage of K-means is that the number of clusters K has no explicit selection criteria and is difficult to estimate. Secondly, it can be seen that every iteration of the K-Means algorithm traverses all the samples, so the time of the algorithm is very expensive. Finally, the K-means algorithm is a distance-based partitioning method. It is only applicable for data sets which are convex and not suitable for clustering nonconvex clusters [6].

2.2.2. Fuzzy C-Means

Fuzzy c-means (FCM) is a clustering method that allows one data to belong to two or more clusters. In other words, each point has a degree of belonging to clusters, as in fuzzy logic, rather than belonging completely to one cluster. Hence, points on the edge of a cluster may be in the cluster to a lesser degree than the points in the center of the cluster [3]. Fuzzy c-means has been a very important tool for image processing in clustering objects in an image the standard FCM divides the image data into c-clusters based on the minimization of the objective function. The FCM objective function can achieve the minimum by updating the cluster centers and the membership functions. Fuzzy segmentation is accomplished iteratively via objective function optimization, with the update of membership and the cluster centers. Since these methods do not consider the spatial information in the image space, it is highly sensitive to imaging faults and noises, and cannot effectively compensate for intensity inhomogeneities. Due to these problems, the efficiency of the FCM method drops significantly in the case of noisy images and artifacts

Algorithm [7]:

1. Select a number of clusters.
2. Assign randomly to each of points in the image coefficients for being in the clusters.

3. Repeat steps 4 and 5 until the algorithm has converged (i.e. the change in the coefficients' value between two iterations is not more than e, which is, the given sensitivity threshold).
4. Compute the centroid of each of the clusters
5. For each point in the image, compute its coefficient of being in the cluster, using the following equation:

$$c_k = \frac{\sum_x w_k(x)^m x}{\sum_x w_k(x)^m}. \qquad \text{(Eq.2)}$$

2.3. Watershed Segmentation

The main principle behind this method comes from geography i.e. from a landscape that is flooded by water, the watersheds are the dividing lines of the regions of falling rainwater. [8]. The watershed method is a morphological gradient-based segmentation procedure. The gradient plot of the image is considered to be a relief map in which different gradient values correspond to different altitudes. If we put a hole in each local minimum and submerge the whole map in the water, the water level will rise over the basins. When two different bodies of water meet, a dam has to be built between them. This development continues until all the points in the map are immersed. Finally, the whole image is segmented by the use of dams which are then called watersheds, and the segmented regions are referred to as catchment basins. A catchment basin is a geographical area that drains into a river or reservoir. The watershed algorithm applies these ideas to a grayscale image in such a way that it can be used to solve a variety of image segmentation problems [9].

The grey-level of the image is visualized as a topographic relief, such that the grey-level of a pixel is thought of as its height in the relief. This basically means that the higher the grey-level of the pixel, the higher the height on the relief, lower the grey-level, lower the height in the relief. Now, suppose a water drop falls on the topographic relief, it flows over a path that finally reaches a local minimum.

In the concept of watersheds, the image is visualized in three dimensions i.e. two spatial coordinates and one intensity coordinate. There are three different types of points a) points of a regional minimum; b) points such that if a drop of water placed at that point will certainly fall at a local minimum; c) points so that water is equally likely to fall to more than one minimum. The points satisfying (b) is called catchment basin or watershed of that minimum. The points satisfying (c) condition are called as watershed lines.

The basic idea is that a hole is punched in each regional minimum and the entire landscape is flooded from below by letting the water rise through the holes at a uniform rate. When the rising water from the different catchment basins is about to merge, a dam is built to prevent the merging. The water flooding will ultimately reach such a stage that only the tops of the dams are visible above the waterline. These dam boundaries resemble the dividing lines of the watersheds. Hence, these are the connected boundaries which are extracted by the watershed segmentation algorithms.There are three basic approaches for watershed segmentation.

2.3.1. Distance transform approach

Distance transform is usually used along with the watershed transform [10]. The job of the distance transform is to calculate the distance from every pixel to the nearest non-zero valued pixel. An image that is binary can be converted to a grey level image, which is then suitable for watershed segmentation using different distance transforms. But, different DT on the same image can produce different effects.

2.3.2. Gradient transform

The gradient magnitude is how fast the image changes. The gradient magnitude is used for preprocessing an image before applying watershed segmentation on it. This image has higher pixel values at the edges and lowers in other parts. Hence, watershed transforms on such images result in watershed ridgelines along the edges [11]. The disadvantage of this method is over-segmentation. The gradient provides a global analysis of the image so that the unwanted contours which are added due to noise are significantly decreased. The over-segmentation problem which occurs with the watershed technique can be reduced so that the segmentation process can be applied using the topological gradient approach. Another advantage is that it separates the segmentation into two steps: first, detect the main edges of the image, second, compute the watershed of the detected gradient [10].

2.3.3. Marker Controlled Methods

This approach is used to control the oversegmentation in images. A marker is a connected component that belongs to an image. Markers are used to adjust the gradient image. Markers can be internal or external. Internal markers are for objects and external markers are for a boundary. Marker controlled segmentation is better for segmenting objects with closed contours, where edges are expressed as ridges. Internal markers are placed inside an object of interest, and external markers are associated with the background. After segmentation is done, the boundaries of the watershed areas are arranged on the desired ridges, hence separating objects from their neighbors [11]. The main disadvantage of this method is oversegmentation due to a large number of local minima. To decrease this effect, the marker-controlled watershed method segments the objects with closed contours. The internal and external markers are defined in the beginning. The boundaries of objects, even if they are not clear are expressed as ridges between two markers and located [12]. In this method, the external marker is obtained manually by drawing a boundary around the object of interest. Now, the internal marker is determined automatically by combining different techniques such as Canny edge detection, thresholding, and morphological operations. The segmentation function is modified such that it has only minima at the foreground and background markers. The watershed method combines elements of both the discontinuity and similarity-based methods. Originally the watershed was used only for grayscale images, is now extended to color images using the computationally efficient form (FIFO queues). The main advantage of this method is that the resulting boundaries from closed and connected regions. And the boundaries of the resulting regions correspond to contours which appear in the image.

2.4 Edge-based segmentation:

An edge (i.e. boundaries which separate distinct regions) is identified by a discontinuity in grey level values. When a pixel's gray level value is similar to its neighbor's grey level value, then it is probably not an edge pixel. But if it's neighboring pixel's values vary widely, then it may signify an edge pixel [13]. The generalized algorithm for edge-based segmentation goes as follows:

1: Apply derivative operator to detect edges of objects in the image.
2: calculate the strength of the edge by evaluating the magnitude of the gradient.
3: Save the edges which have a magnitude greater than the threshold value T.

4: Find the location of the crack edge. This edge is either accepted or discarded by the confidence it receives from its predecessor and successor edges.
5: Repeat 3 and 4 with different threshold values to find closed boundaries [14]

Steps for edge detection [15]
1. Smoothing: used to suppress noise, without destroying true edges.
2. Enhancement: a filter is applied to improve the quality of the edges (sharpening)
3. Detection: Decide which edges should be discarded and which edges should be retained
4. Localization: Determine the location of the edge

There are various edge detecting algorithms. The majority of the edge detecting algorithms may be characterized in these categories:
Gradient: In this method, the edges are detected in an image by analyzing the maximum and minimum values in the first derivative of the image. Roberts, Prewitt, Sobel edge operators are some examples of this method.
Laplacian: This method searches for zero crossings (the point where the Laplacian changes sign) in the second derivative of the image. This is the point where the edge may be found. Marr Hildreth, Laplacian of Gaussian are some examples of this method.

2.3.1 Sobel Edge operator

Sobel operator does a 2D spatial gradient measurement on the image such that the regions of high spatial frequency that represent edges are emphasized. Usually, it fins the approximate absolute gradient magnitude at each point in the image. The operator has a pair of 3x3 convolution kernels as shown in Fig.1.

+1	+2	+1
0	0	0
-1	-2	-1

Gx

-1	0	+1
-2	0	+2
-1	0	+1

Gy

Fig 1. Sobel operator

This shows that the outcome of the Sobel operator at a point which is in a region of constant intensity is a zero vector and at a point on an edge is a vector which points across the edge, from darker to brighter values. Segmented image given by Sobel operator gives proper edges for texture variation.

2.3.2. Prewitt operator

In this method, the maximum response of a set of convolution kernels is calculated such that it finds the local edge direction of each pixel, hence this operator is appropriate to estimate the magnitude and direction of each pixel. Even though differential gradient edge detection to estimate the orientation of the edge from the magnitudes in the x and y directions is time consuming task. For this operator one kernel is very sensitive to the edges in the vertical direction and one to the horizontal direction as shown in Fig 2

+1	+1	+1
0	0	0
-1	-1	-1

Gx

-1	0	+1
-1	0	+1
-1	0	+1

Gy

Fig 2. Prewitt operator

2.3.3. Kirsch edge operator

In this method edges are detected using eight filters which are applied to the image and the maximum is retained for the final image. The eight filters are just a rotation of the basic compass convolution filter. The edge magnitude is the maximum value found by convolution of each mask with the image. The direction is defined by mask that produces the maximum magnitude as shown in Fig.3. Example, mask H1 corresponds to a vertical edge, while mask H6 corresponds to a diagonal edge.

$$\underset{\text{East}}{H_1}=\begin{bmatrix}5 & -3 & -3\\ 5 & 0 & -3\\ 5 & -3 & -3\end{bmatrix}\quad \underset{\text{Northeast}}{H_2}=\begin{bmatrix}-3 & -3 & -3\\ 5 & 0 & -3\\ 5 & 5 & -3\end{bmatrix}\quad \underset{\text{North}}{H_3}=\begin{bmatrix}-3 & -3 & -3\\ -3 & 0 & -3\\ 5 & 5 & 5\end{bmatrix}\quad \underset{\text{Northwest}}{H_4}=\begin{bmatrix}-3 & -3 & -3\\ -3 & 0 & 5\\ -3 & 5 & 5\end{bmatrix}$$

$$\underset{\text{West}}{H_5}=\begin{bmatrix}-3 & -3 & 5\\ -3 & 0 & 5\\ -3 & -3 & 5\end{bmatrix}\quad \underset{\text{Southwest}}{H_6}=\begin{bmatrix}-3 & 5 & 5\\ -3 & 0 & 5\\ -3 & -3 & -3\end{bmatrix}\quad \underset{\text{South}}{H_7}=\begin{bmatrix}5 & 5 & 5\\ -3 & 0 & -3\\ -3 & -3 & -3\end{bmatrix}\quad \underset{\text{Southeast}}{H_8}=\begin{bmatrix}5 & 5 & -3\\ 5 & 0 & -3\\ -3 & -3 & -3\end{bmatrix}$$

Fig.3. Kirsch edge detector

2.3.4. Roberts edge detection

This operator performs a simple and quick 2d spatial gradient measurement on an image. Hence, it emphasizes the regions of high spatial frequency which may often correspond to an edge. Commonly, both the input and output images are grayscale images. Pixel values at each point in the result signify the estimated absolute magnitude of the spatial gradient of the input image at that point [16]. Figure 4 shows the Roberts Edge detection

-1	0
0	+1

G_x

0	-1
+1	0

G_y

Fig.4. Roberts edge detection

Gradient based classical operators like Robert, Prewitt, Sobel were primarily used for edge detection but they did not give sharp edges and were highly sensitive to noise image.

2.3.5. LoG edge detection

The LoG of an image f(x,y) is a second order derivative defined by eq.3.

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2} \qquad \text{(Eq.3)}$$

It does two things. First, smoothens the image. Second, it calculates the Laplacian, which gives a double edge image. For locating the edges, the zero crossings between the double edges is found. LoG is implemented using the mask in Fig.5.

0	-1	0
-1	4	-1
0	-1	0

G_x

-1	-1	-1
-1	8	-1
-1	-1	-1

G_y

Fig.5: LoG edge detection

2.3.5. Marr Hildrith Edge detection

This edge detector was popular before Canny proposed his algorithm. It is a gradient-based edge detector that uses Laplacian to take the second derivative of an image. It works by finding the zero crossings [17]. It uses both Gaussian and Laplacian operators so the Gaussian operator reduces noise and the Laplacian operator detects the sharp edges. This operator has two limitations: high probability of detecting false edges and localization error increases at curved edges.

III. DISCUSSION

On observing these techniques, edge detection techniques can be used when there are a lot of objects in an image or when the image has a lot of fine features to segment. Thresholding method is good to be used when the image has a few features such as medical images. Clustering techniques are good for segmentation color images and watershed technique is good for color images with few features.

IV. CONCLUSION

In this paper, different image segmentation techniques that are used for the purpose of medical image analysis are discussed. It is seen that there is no perfect method for performing perfect image segmentation because the result of image segmentation depends on many factors, i.e., pixel color, texture, intensity and problem domain. Therefore, it is not possible to consider a one single method for all type of images, neither can all the methods perform well for a particular type of image. Hence, it may be good to use multiple methods as a hybrid for various image segmentation problems.

References

[1] HTTPS://MEDIUM.COM/@HBYACADEMIC/OTSU-THRESHOLDING-4337710DC519

[2] Pallavi Tambe, Jenitor Thomson, Neha Surti. 2016. Comparative Study of Segmentation Techniques for Brain Tumor Detection, IJERT, Vol. 5 Issue 02, February-2016

[3] Ajala Funmilola A*, Oke O.A, Adedeji T.O, Alade O.M, Adewusi E.A. 2012. Fuzzy k-c-me ans Clustering Algorithm for Medical Image Segmentation, Journal of Information Engineering and Applications, ISSN 2224-5782 (print) ISSN 2225-0506 (online) Vol 2, No.6, 2012

[4] Dilpreet Kaur, Yadwinder Kaur, Various Image Segmentation Techniques: A Review, International Journal of Computer Science and Mobile Computing, IJCSMC, Vol. 3, Issue. 5, May 2014, pg.809 – 814

[5] Sepideh Yazdani, Rubiyah Yusof, Mohsen Pashna, Image Segmentation Methods and Applications in MRI Brain Images, IETE TECHNICAL REVIEW | 2015

[6] Song Yuheng, Yan Hao, SiChuan, ChengDu, Image Segmentation Algorithms Overview

[7] G.Vasavi and Dr. S Jyothi, Medical Image Segmentation and Clustering methods and applications –A Survey, International Journal of Latest Trends in Engineering and Technology IJLTET Special Issue- ICRACSC-2016, pp.099-102 e-ISSN: 2278-621X

[8] Thodeti Srikanth, Prof P.Pradeep Kumar, Ashwin Kumar, Color Image Segmentation using Watershed Algorithm, International Journal of Computer Science and Information Technologies, Vol. 2 (5) , 2011, 2332-2334

[9] Tara Saikumar, P. Yugander, P. S. Murthy, and B. Smitha, Member, IACSIT, Image Segmentation Algorithm Using Watershed Transform and Fuzzy C-Means Clustering on Level Set Method, International Journal of Computer Theory and Engineering, Vol. 5, No. 2, April 2013

[10] Amandeep Kaur, Aayushi, Image Segmentation Using Watershed Transform, International Journal of Soft Computing and Engineering (IJSCE) ISSN: 2231-2307, Volume-4, Issue-1, March 2014

[11] Arindrajit Seal, Arunava Das, Prasad Sen, Watershed: An Image Segmentation Approach, International Journal of Computer Science and Information Technologies, Vol. 6 (3) , 2015, 2295-2297

[12] Lalitha K, Amrutha R, Stafford Michahial, Implementation of Watershed Segmentation International Journal of Advanced Research in Computer and Communication Engineering ISO 3297:2007 Certified Vol. 5, Issue 12, December 2016

[13] Zolqernine Othman, Habibollah Haron, Mohammed Rafiq Abdul Kadir, Comparison of Canny and Sobel Edge Detection in MRI Images

[14] P.K.Srimani, Shanthi Mahesh, A Comparative Study of Different Segmentation Techniques for Brain Tumour Detection, International Journal of Emerging Technologies in Computational and Applied Sciences(IJETCAS)

[14] Edge detection (Trucco, Chapt 4 AND Jain et al., Chapt 5)

[15] Srinivas B.L.,Hemalatha, Jeevan K.A, Edge Detection Techniques for Image Segmentation, International Journal of Innovative Research in Computer and Communication Engineering, (An ISO 3297: 2007 Certified Organization) Vol. 3, Special Issue 7, October 2015

[16] Rashmi, Mukesh Kumar and Rohini Saxena, Algorithm and technique on various edge detection: a survey, signal & image processing: An International Journal (SIPIJ) Vol.4, No.3, June 2013

[17] Muthukrishnan.R, M.Radha, Edge detection techniques for image segmentation, International Journal of Computer Science & Information Technology (IJCSIT) Vol 3, No 6, Dec 2011