

January 2013

PERFORMANCE COMPARISON ON MEDICAL IMAGE SEGMENTATION ALGORITHMS

MANOJ KUMAR V

Bannari Amman Institute of Technology, Sathyamangalam, manojpudunagaram@gmail.com

SUMITHRA M. G

*ECE Department Bannari Amman Institute of Technology, Sathyamangalam, TamilNadu,
mgsumithra@rediffmail.com*

Follow this and additional works at: <https://www.interscience.in/ijipvs>



Part of the [Robotics Commons](#), [Signal Processing Commons](#), and the [Systems and Communications Commons](#)

Recommended Citation

KUMAR V, MANOJ and G, SUMITHRA M. (2013) "PERFORMANCE COMPARISON ON MEDICAL IMAGE SEGMENTATION ALGORITHMS," *International Journal of Image Processing and Vision Science*: Vol. 1 : Iss. 3 , Article 14.

DOI: 10.47893/IJIPVS.2013.1041

Available at: <https://www.interscience.in/ijipvs/vol1/iss3/14>

This Article is brought to you for free and open access by the Interscience Journals at Interscience Research Network. It has been accepted for inclusion in International Journal of Image Processing and Vision Science by an authorized editor of Interscience Research Network. For more information, please contact sritampatnaik@gmail.com.

PERFORMANCE COMPARISON ON MEDICAL IMAGE SEGMENTATION ALGORITHMS

MANOJ KUMAR V¹ & SUMITHRA M G²

^{1,2}Bannari Amman Institute of Technology, Sathyamangalam
Email:manojpudunagaram@gmail.com, mgsumithra@rediffmail.com

Abstract- Image segmentation plays a crucial role in many medical-imaging applications, by automating or facilitating the delineation of anatomical structures and other regions of interest. In this paper explaining current segmentation approaches in medical image segmentation and then reviewed with an emphasis on the advantages and disadvantages of these methods and showing the implemented outcomes of the thresholding, clustering, region growing segmentation algorithm for the brain MRI and also explaining the edge detection of retinal image.

Keywords- Image segmentation, thresholding, clustering, region growing, edge detection.

I. INTRODUCTION

Medical imaging is a valuable tool in medicine. Computed Tomography(CT), Magnetic Resonance Imaging(MRI), Ultra Sound imaging(US) and other imaging techniques provide more effective information about the anatomy of the human body. These technologies become more critical in diagnosis and treatment planning. Some computer algorithms are applying for the description of anatomical structures and other regions of interest are becoming increasingly important in assisting and automating specific radiological tasks. These algorithms, called image segmentation algorithms, play a vital role in numerous biomedical-imaging applications, such as study anatomical structure, Identify Region of Interest i.e. locate tumour and other abnormalities, Measure tissue volume to measure growth of tumour (also decrease in size of tumour with treatment), Help in treatment planning prior to radiation therapy; in radiation dose calculation [1].

Segmentation is the process of partitioning an image into multiple segments. The segmentation is to simplify and/or change the representation of an image into other form that is more significant and easier to analyse.

Even though a number of algorithms have been proposed in the field of medical image segmentation, medical image segmentation continues to be a complex and challenging problem. At present, various methods using are, Thresholding, Clustering methods Compression-based methods, Histogram-based methods, Edge detection, Region-growing methods, Split-and-merge methods, Partial differential equation-based methods, Graph partitioning methods, Watershed transformation, Model based segmentation Multi-scale segmentation, Neural networks segmentation [1].

This paper is organized as follows. Section II describes the widely using image segmentation algorithms, Section III discuss the experimental results of various segmentation algorithms. In Section IV, validation parameter to be considered is explained. In Section V conclusion of paper is discussed.

II. IMAGE SEGMENTATION ALGORITHMS

A. Thresholding

Thresholding is the simplest method of image segmentation. This method is based on a threshold value to turn a gray-scale image into a binary image [2]. In this method image is segmenting by comparing pixel values with the predefined threshold limit L [3].The following equation defining the threshold level.

Let $X(i,j)$ be an image

$$X(i,j) = \begin{cases} 0, n(i,j) < L \\ 1, n(i,j) \geq L \end{cases} \quad (1)$$

where $n(i,j)$ is the pixel value at the position (i,j) . Thresholding is called adaptive thresholding when a different threshold is used for different regions in the image [4]. thresholding methods can be classified into the following six groups based on the algorithm manipulation . Histogram shape-based methods, clustering-based methods, entropy-based methods, object attribute-based methods, spatial methods, local methods.

B. Clustering method

This is an iterative technique that is used to partition an image into clusters. procedure of clustering method is explained in fig. 1.

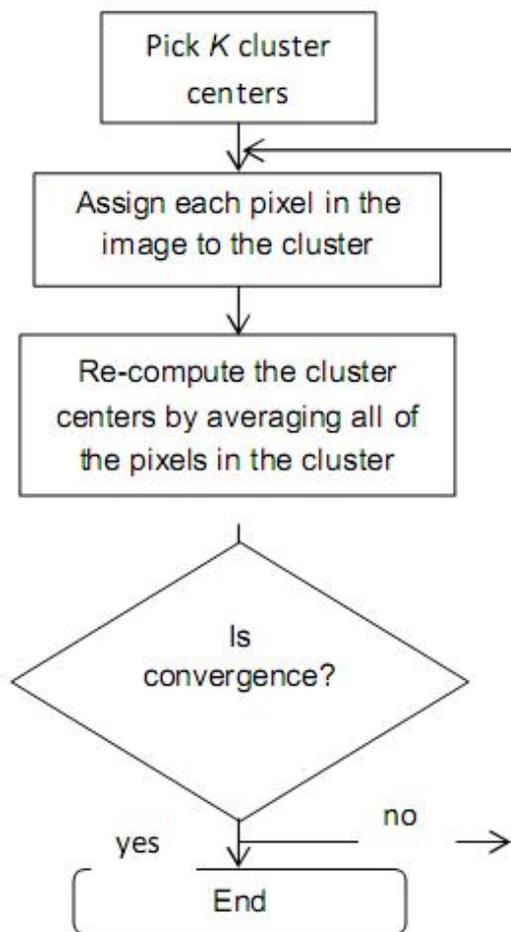


Fig.1. Flow chart showing computation of clustering method.

Clusters can be selected manually, randomly, or based on some conditions. distance between the pixel and cluster center is calculated by the squared or absolute difference between a pixel and a cluster center. The difference is typically based on pixel colour, intensity, texture, and location, or a weighted combination of these factors. More commonly used clustering algorithms are K – means algorithm, fuzzy c-means algorithm, expectation – maximization (EM) algorithm [1].

The quality of the final result of the clustering method depends mainly on the initial set of clusters. Since the algorithm is extremely fast, a collective method is to run the algorithm several times and select the best clustering. A drawback of the clustering algorithm is that the number of clusters k is an input parameter. A wrong choice of k may yield poor results. The algorithm also assumes that the variance is an appropriate measure of cluster scatter.

C. Compression – based method

Compression based method is an optimum segmentation method, because this is the one that minimizes the coding length of the data over all other possible segmentation techniques [5]. The

relationship between compression and segmentation is that, segmentation tries to find patterns in an image and any regularity in the image can be used to compress it. And this method describes each segment by its texture and boundary shape. Each of these components is modelled by a probability distribution function [6].

This method yields the number of bits required to encode that image based on the given segmentation. Thus, among all possible segmentations of an image, this segmentation procedure produces the shortest coding length.

This can be achieved by a simple agglomerative clustering method. The distortion in the lossy compression determines the unevenness of the segmentation and its optimal value may differ for each image. This parameter can be estimated heuristically from the contrast of textures in an image.

D. Histogram – based method

In this method, a histogram is computed from all of the pixels in the image, and the peaks and valleys in the histogram are used to locate the clusters in the image [4]. Colour or intensity can be used as the parameters for the measure. Since the histogram-based methods are very efficient when compared to other image segmentation methods because they typically require only one pass through the pixels.

In mathematical sense, a histogram is a function X_i that counts the number of observations that fall into each of the disjoint categories which is known as *bins*, whereas the graph of a histogram is merely one way to represent a histogram. Thus, if we let N be the total number of observations and l be the total number of bins, the histogram X_j meets the following conditions (Karl Pearson):

$$N = \sum_{j=1}^l X_j \quad (2)$$

An improvement can be made in this technique by recursively apply the histogram method to every clusters in the image in order to divide image into smaller clusters [7], [8]. This is repeating until no more clusters are formed. One disadvantage of the histogram-seeking method is that it may be difficult to identify significant peaks and valleys in the image [4].

Histogram-based approaches can also be quickly applicable over multiple frames, while maintaining their single pass efficiency. The same approach that is done with single frame can be applied to multiple frame, and after the results are merged, peaks and valleys that were previously difficult to identify are more likely to be distinguishable. The histogram based method can also be applied on a per pixel level, and the information result are used to determine the most frequent colour for the pixel location.

E. Edge detection

The edge-based approaches is to detect the object boundaries by using an edge detection operator and then extract boundaries by using the edge information [9]. The problem of edge detection is the presence of noise that results in random variation in level from pixel to pixel. Therefore, the ideal edges are never encountered in real images because of noise [9]. A great diversity of edge detection algorithms have been devised with differences in their mathematical and algorithmic proper-ties such as Roberts, Sobel, Prewitt, Laplacian, and Canny, all of which are based on the difference of gray levels [9]. The difference of gray levels can be used to detect the discontinuity of gray levels.

Although many algorithms for boundary detection have been developed to achieve good performance in field of image processing, most algorithms for detecting the correct boundaries of objects have difficulties in medical images in which ill-defined edges are encountered [9]. Medical images are often noisy and too complex to expect local, low level operations to generate perfect primitives. The complexity of medical images makes the correct boundary detection very difficult.

F. Region-growing method

The region growing is a mostly used classical segmentation method. These region growing based segmentation models shares the following assumption about the image pixel properties [3]. The intensity values within each region/object conforms to Gaussian distribution, The mean intensity value for each region/object is different.

Region growing is a technique for extracting an image region that is connected based on some predefined criteria. These criteria can be based on intensity information and/or edges in the image [1]. One example for the region growing method is seeded region growing. The procedure for the same as follows:

1. This method takes a set of seeds as input along with the image.
2. The seeds mark each of the objects to be segmented.
3. The regions are iteratively grown by comparing all unallocated neighbouring pixels to the regions.
4. The difference between a pixel's intensity value and the region's mean, δ , is used as a measure of similarity.
5. The pixel with the smallest difference measured this way is allocated to the respective region.
6. This process continues until all pixels are allocated to a region.

The primary disadvantage of region growing is that it requires manual interaction to obtain the seed point. Split-and-merge is an algorithm related to region growing, but it does not require a seed point. Region growing can also be sensitive to noise, causing extracted regions to have holes.

G. Split and merge method

Split and merge method also called as quad - tree segmentation, because split-and-merge segmentation is based on a quad-tree partition of an image. The process of split and merge segmentation method is explained as follow in fig. 2:

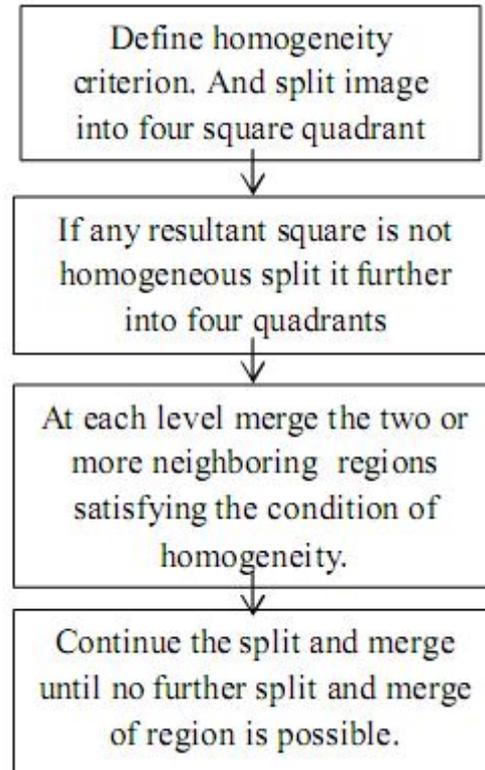


Fig.2. The flowchart of split and merge method.

This is the combination of splits and merges utilizing the advantage of the two methods. This method starts at the root of the tree that represents the whole image. If it is found non-uniform (not homogeneous), then it is split into four son-squares (the splitting process), and so on so forth. Conversely, if four son-squares are homogeneous, they can be merged as several connected components (the merging process). The node in the tree is a segmented node. This process continues recursively until no further splits or merges are possible. When a special data structure is involved in the implementation of the algorithm of the method, its time complexity can reach $O(n \log n)$, an optimal algorithm of the method [1].

H. Graph partitioning methods

Graph partitioning methods can effectively be used for image segmentation. In these methods, the image is modelled as a weighted, undirected graph. Usually a pixel or a group of pixels are associated with nodes and edge weights define the (dis)similarity between the neighbourhood pixels. The graph (image) is then partitioned according to a criterion designed to model "good" clusters. Each partition of the nodes (pixels) output from these

algorithms are considered an object segment in the image. Some popular algorithms of this category are normalized cuts, random walker, minimum cut, isoperimetric partitioning, minimum spanning tree-based segmentation.

This graph partitioning algorithm is perfectly adapted to a volume binary classification issue [10]. Moreover, the transcription of a segmentation issue into an energy minimization framework makes it possible to encode various characteristics of the data: classification training, degree of similarity between voxels of the same class (region-based approaches), changes between classes (boundary-based approaches), etc.

Once the graph is built, correct weight is assigned to each links according to some relevant cost functions, graph cuts algorithm, the regional term cost function is defined after an interactive process [10]. Histograms are built from this labelling and probability density functions are extracted for each class and encoded in the graph. Graph cut segmentation can be formulated as an energy minimization problem such that for a set of pixels P and a set of labels L, the goal is to find a labelling f: P→L that minimizes the energy function E(f) [10].

$$E(f) = \sum_{p \in P} R_p(f_p) + \sum_{p \in P, q \in N_p} B_{p,q}(f_p, f_q) \quad (3)$$

where N_p is the set of pixels in the neighbourhood of p, $R_p(f_p)$ is the cost of assigning label $f_p \in L$ to P, and $B_{p,q}(f_p, f_q)$ is the cost of assigning labels $f_p, f_q \in L$ to p and q.

I. Neural networks segmentation

Inspired by the way biological nervous systems such as human brains process information, an artificial neural network (ANN) is an information processing system which contains a large number of highly interconnected processing neurons [11]. These neurons work together in a distributed manner to learn from the input information, to coordinate internal processing, and to optimise its final output.

The basic structure of a neuron can be theoretically modelled as shown in fig. 3 where X { x_1, x_2, \dots, x_n } represent the inputs to the neuron and Y represents the output. Each input is multiplied by its weight w_i , a bias b is associated with each neuron and their sum goes through a transfer function f [11].

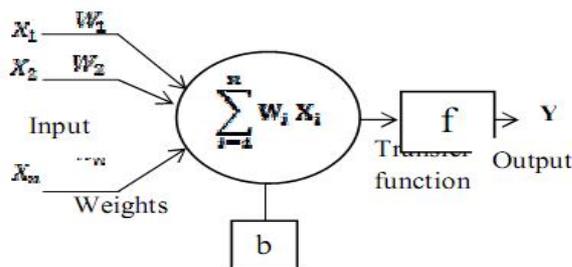


Fig.3. The model of neuron

Neural Network segmentation relies on processing small areas of an image using an artificial neural network or a set of neural network. There are several different neural network architectures available for medical imaging applications, Feed-forward Network, Radial Basis Function Networks, Feed-back Network, Self-Organising Map [11].

Each neuron in the network corresponds to one pixel in an input image, receiving its corresponding pixel's color information (e.g. intensity) as an external stimulus. Each neuron also connects with its neighboring neurons, receiving local stimuli from them. The external and local stimuli are combined in an internal activation system, which accumulates the stimuli until it exceeds a dynamic threshold, resulting in a pulse output. Through iterative computation, pulse coupled neural network neurons produce temporal series of pulse outputs. The temporal series of pulse outputs contain information of input images and can be utilized for various image processing applications, such as image segmentation and feature generation.

J. Shortcomings of Segmentation Methods

Segmentation of medical images is a difficult task as medical images are complex in nature and rarely have any simple linear feature. Further, the output of segmentation algorithm is affected due to, Partial volume effect, Intensity inhomogeneity, Presence of artifacts, Closeness in gray level of different soft tissue.

Medical images are often noisy and too complex to expect local, low level operations to generate perfect primitives. Medical imaging technique like ultra sound, CT may contain echo perturbations and speckle noise, it may affect the segmentation.

III. EXPERIMENTAL RESULTS

In this section discussing the implementation of various segmentation algorithms for the MRI of brain, And edge detection of retinal image.

A. Thresholding

This method is based on threshold value.

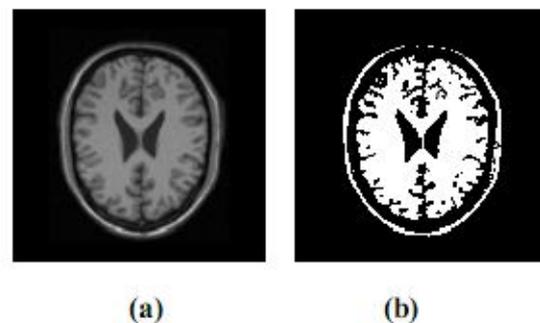


Fig .4. Segmentation of brain MRI using thresholding. (a) original (b) segmented image

This best segmentation obtained for the threshold value 0.384. Selection of threshold value should be correct otherwise output will not be a good segmented one.

B. Clustering method

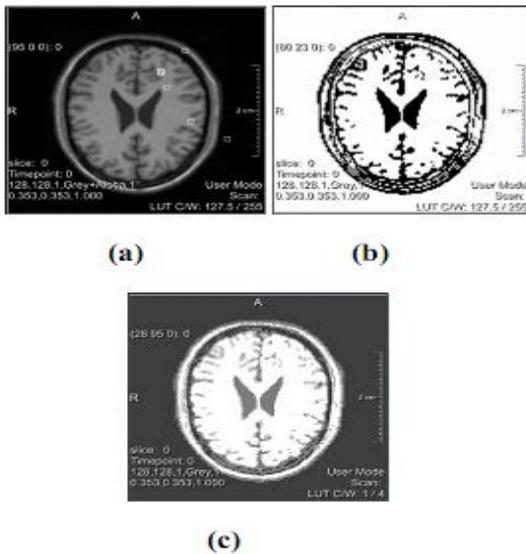


Fig.5. Clustering segmentation method.(a) original image,(b) and (c) segmented output

In this example value of cluster center 3.8057, Iteration limit given is 1000, and number of iterations performed is 4.

C. Region-growing method

Region growing is a technique for extracting an image region that is connected based on some predefined criteria. These criteria can be based on intensity information and/or edges in the image. The seeds mark each of the objects to be segmented. The primary disadvantage of region growing is that it requires manual interaction to obtain the seed point.

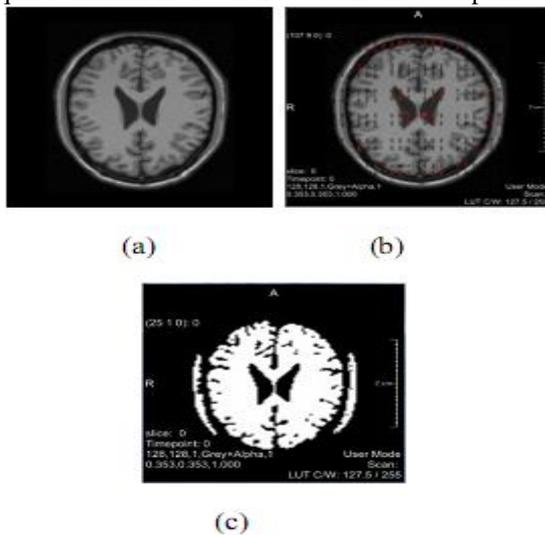


Fig.6. Region growing segmentation. (a)original image, (b) image with seed points, (c) segmented image.

D. Edge detection

Due to the presence of intensity inhomogeneity and closeness in gray level of different tissue, edge detection cannot be done in MRI brain image [1].

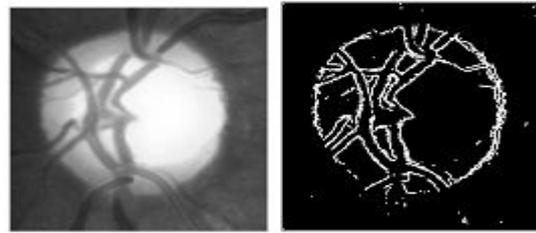


Fig.7. Edge detection operation

The difference of gray levels can be used to detect the discontinuity of gray levels, which is used to detect the object boundary.

IV. VALIDATION

To quantify the performance of a segmentation method, validation experiments are necessary. The most straightforward approach to validation is to compare the automated segmentations with manually obtained segmentations. Other common approach to validating segmentation methods is through the use of physical phantoms or computational phantoms. Specificity, sensitivity, and accuracy are the other parameters to be considered.

V. CONCLUSION

Image segmentation plays a crucial role in many medical-imaging applications, by automating or facilitating the delineation of anatomical structures and other regions of interest. Many methods are existing and still developing the new methods for the segmentation to overcome the shortcomings of the existing methods. Here various segmentation methods have implemented on brain MRI and edge detection on retinal image. Outcomes are depend on some input parameter like, threshold for the thresholding, number of cluster centres, and seed point for the region growing method. Region growing needs manual interaction. Running time for the clustering method depends on the number of iteration used. Edge detection depends on discontinuity of gray level and on intensity variation on the gray scale images. Above explained methods are gives almost identical outcomes, when the inputs are accurate.

REFERENCE

[1] Dzung L. Pham, Chenyang Xu, and Jerry L. Prince, "Current Methods In Medical Image Segmentation," Department of Electrical and Computer Engineering, The Johns Hopkins University, Annu. Rev. Biomed. Eng. 2000. 02:315–37.

- [2] K J. Batenburg, and J. Sijbers, "Adaptive thresholding of tomograms by projection distance minimization", *Pattern Recognition*, vol. 42, no. 10, pp. 2297-2305, APRIL, 2009.
- [3] Tranos Zuva, Oludayo O, Olugbara, Sunday O. Ojo and Seleman M Ngwira, "Image Segmentation, Available Techniques, Developments and Open Issues," *Canadian Journal on Image Processing and Computer Vision* Vol. 2, No. 3, MARCH 2011.
- [4] Shapiro, Linda G and stockman, George C.(2002). *Computer Vision*. prentice hall. ISBN 0-13-030796-3.
- [5] Hossein Mobahi, Shankar Rao, Allen Yang, Shankar Sastry and Yi Ma. "Segmentation of Natural Images by Texture and Boundary Compression", *International Journal of Computer Vision (IJCV)*, 95 (1), pg. 86-98, OCT. 2011.
- [6] Shankar Rao, Hossein Mobahi, Allen Yang, Shankar Sastry and Yi Ma, "Natural Image Segmentation with Adaptive Texture and Boundary Encoding", *Proceedings of the Asian Conference on Computer Vision (ACCV) 2009*, H. Zha, R.-i. Taniguchi, and S. Maybank (Eds.), Part I, LNCS 5994, pp. 135--146, Springer.
- [7] Alireza khotanzad and Abdelmajid bouarfa *Image Processing and Analysis Laboratory, Electrical Engineering Department, Southern Methodist university, Dallas, Texas 75275, U.S.A.* publication 29 January 1990.
- [8] Ohlander, Ron, Price, Keith, Reddy, D. Raj (1978). "Picture Segmentation Using a Recursive Region Splitting Method". *Computer Graphics and Image Processing* 8 (3): 313-333.
- [9] Krit Somkantha, Nipon Theera-Umpon, and Sansanee Auephanwiriyaikul, "Boundary Detection in Medical Images Using Edge Following Algorithm Based on Intensity Gradient and Texture Gradient Features" *IEEE Transactions on Biomedical Engineering*, vol. 58, no. 3, march 2011.
- [10] Xinjian Chen, Jayaram K. Udupa Ulas Bagc , Ying Zhuge and Jianhua Yao, "Medical Image Segmentation by Combining Graph Cut and Oriented Active Appearance Models".
- [11] J. Jiang, P. Trundle and J. Ren, *Digital Media & Systems Research Institute, University of Bradford*, "Medical Image Analysis with Artificial Neural Networks".

