Survey of Medical Image Segmentation Methods CS554 Survey Report

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***Abstract*—Image segmentation plays a vital role in various tasks ranging from image preprocessing to object recognition and tracking. Until today, many methods are present that can extract the required foreground from the background. However, with advanced deep learning, many segmentation tasks are done solely by training a network for a specific dataset. Nonetheless, such methods are hindered by their training datasets distribution. Classical works, however, are generally not hindered by such problems. Here, we summarize the classical segmentation methods that are used for medical image analysis.**

***Index Terms*—Computer Vision, Segmentation, Medical Imaging, Graph-Cut, Watershed, Clustering, Random Fields**

I. Introduction

IMAGE segmentation plays a crucial role in many industries as its primary goal is to simplify and/or change the representation of an image into something more meaningful and easier to analyze. The usage of segmentation is even crucial in clinics where the segmentation of a medical image provides valuable information, such as the 3D structure of a tissue or automation of targeting malignant tissues such as tumors. Its popularity among clinics is even more relevant after the rise of deep learning techniques. Nonetheless, classic methods are still prevalent and can be utilized when deep learning models fail. The classical models are especially more powerful when there is not enough training data, or the training dataset has a specific distribution which can lead to bias in the model. Conventionally, segmentation can be grouped into five categories, and also a combination of such methods is further discussed in the following sections.

II. Classic Segmentation Methods

A. Threshold-Based Segmentation

The first method is the threshold/cluster-based segmentation method [1]. This method usually divides the image into two parts, namely foreground, and background. When the intensity of the pixels is larger/smaller than a predefined threshold, those pixels are classified as foreground. Threshold-based approaches are the simplest, easiest, and fast among all the existing segmentation methods. However, finding an appropriate threshold that can directly separate the image into two groups is not easy, and due to noise and other artifacts, segmentation might not be the best.

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B. Edge-Based Segmentation

The second method is the edge-based segmentation method [1]. Edge-based segmentation algorithms identify edges based on contrast, texture, color, and saturation variations. This method assumes that the values of the pixels connecting the foreground and background are distinct. The first or second-order derivatives, a method like a gradient, usually detect these discontinuities. Typical edge detection techniques involve a 2D filter, which is made to be sensitive to large gradients. Numerous edge detection operators are described in the literature, each designed to be sensitive to specific types of edges. Nonetheless, each model is still sensitive to the noise in the image. Thus, an algorithm for edge detection should remove the noise so that it would not be recognized as an edge. Otherwise, noisy images common in medical imaging cannot be used for such a model [2]. An example process that is taken from Canny Edge Detector can be as follows.

1) A gaussian low-pass filter is used as the first step in the Canny detector to smooth the image to remove or attenuate the noise.
2) Estimate gradients and based on gradient magnitude and direction, edges are sharpened.
3) The Sobel kernel calculates the gradient, which is applied to each pixel in the image in both directions.
4) The strength of the edge is determined by gradient magnitude, while the direction of the gradient is used to determine for each pixel the direction with the largest change in intensity.

As we can see from the process, The performance of the algorithm depends heavily on threshold values, and parameters of the deblurring filter [2]. Furthermore, although these proposed methods can detect the object's boundary, many false edges will be included. Thus, post-processing operations are usually needed for edge-based segmentation [3].

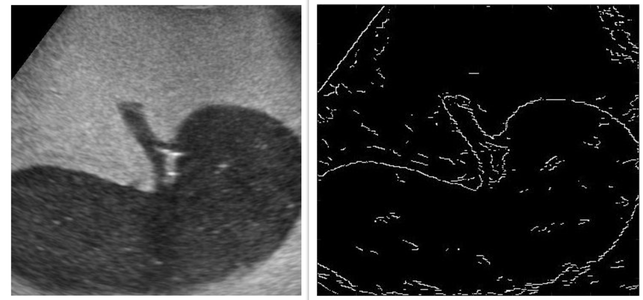

Fig. 1. Segmentation of Kidney Phantom from Ultrasound using Canny Edge Detector [3]

C. Region-Based Segmentation

The following method is called region-based segmentation. The typical algorithms are region-growing, and region-splitting-merging [3]. For the region growing scheme, a set of seeds must be identified first. Then, the neighboring pixels are grouped into these seeds through predefined criteria such as by similar intensity, color, or texture. Hence, the skill of selecting seed points is very important. For the region splitting-merging method, an image is first divided into a series of small regions. Then merge or split these smaller regions by a prerequisite condition. The procedure can be described as splitting the image into many non-overlapped regions until it cannot be split anymore. Then, merge the adjacent regions that satisfy a predefined condition. Region-based segmentation strongly relies on the intensity value of the object and background, and it always produces a non-smooth boundary for the extracted object.

In general clustering algorithms, each pixel in the image has a feature that helps us to detect those points. They can be pixel position, the pixel value if it is a gray image. The pixel value has 3 red, green, and blue features if it is an RGB image. These features are extracted from the image using simple algorithms and some built-in functions; edges, gradients, and gradient direction information are added to the feature space. In segmentation, the number of clusters is given as input with the image. In the algorithm, initial cluster means can be determined using two different initializations, uniform, and random. Then, using the L1 norm, determine the new cluster mean through some iterations. When the change of meaning is under the threshold, the iterations finish, and the last means is determined as the cluster's mean. The advantage of this algorithm is that the segmentation is so fast that the duration is not exceeding about 1 second. The drawback of the method is that the cluster number must be given. So, the results can be under, or over-segmented [4].

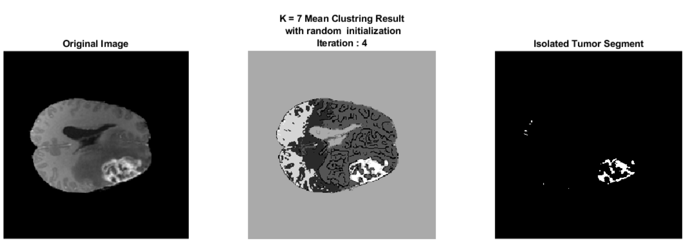

Fig. 2. K-means Algorithm implemented on an MRI image.

D. Watershed-Based Segmentation

Watershed-based segmentation is to find the ridge line called watershed within the image. So, to extract the object, the watershed transform algorithm is usually applied to the gradient image. The simple idea of watershed segmentation can be considered as follows. Consider immersing the landscape in a lake, with water being allowed to enter through the regional minima. Each regional minimum corresponds to a lake, with adjacent lakes meeting at watershed lines as flooding continues [5].

However, the direct application of the watershed algorithm will have an over-segmentation problem due to the noise and other local irregularities of the gradient [3],[6]. There are some approaches to dealing with the over-segmentation issue, such as removing regional minima by prefiltering or merging regions using minimum description length [5]. Marker-controlled watershed segmentation is proposed to reduce over-segmentation. In this method, the regional minimal values only occur at the location of the markers. Thus, the critical procedure is to identify the markers, which include internal and external markers. Internal markers denote the object, while external markers represent the background, and these external markers must be connected [5],[6].

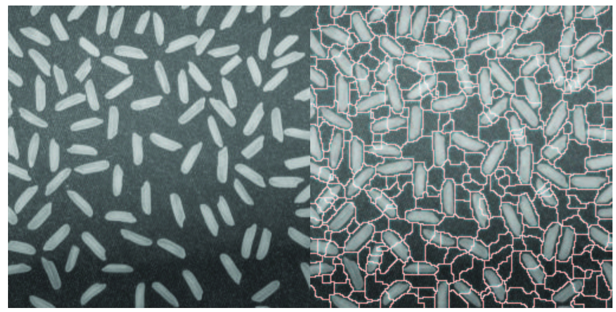

Fig. 3. Watershed Algorithm implemented on an example image [6].

Despite its over-segmentation problem, a watershed can still be utilized for a super-pixel formulation which can then be fed into another segmentation algorithm. A combination of such methods will be further discussed in the following sections.

E. Energy-Based Segmentation

The final method is called Energy-based Segmentation. This method needs to establish an objective (energy) function which will reach a minimum value when the image is segmented as the expected result. One of the most popular algorithms, graph cut, is grouped into this category [3]. For the graph cut segmentation, the energy function is constructed based on regional and boundary information, and it can achieve globally optimal results. Graph-cut segmentation was first proposed by Boykov, and Jolly [7]. Since then, many varied methods based on graph-cut are developed, and these approaches are widely used in medical images. Furthermore, segmentation algorithms such as conditional random fields and Markov random fields are also a subset of energy-based segmentation algorithms.

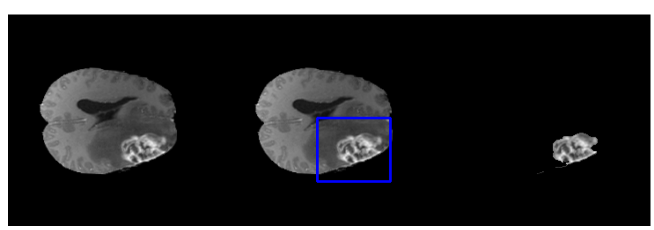

Fig. 4. GraphCut Algorithm implemented on an MRI image.

In this survey, we will first focus on some of the leading hybrid segmentation algorithms and their application in medical image segmentation.

III. Hybrid Segmentation Methods

Before the advancement of deep learning algorithms, to achieve higher segmentation accuracy, researchers came up with hybrid segmentation methods where they mix and match various classical segmentation methods for better performance.

A. Hybrid Watershed and Graph Cut Segmentation

In medical imaging, intense noise, poor gray-scale contrast, and blurred tissue margins are typical [8]. Thus, classical computer vision algorithms without any deep learning model are challenging. A combination of the watershed algorithm with the Grab Cut has been proposed to overcome such a problem. This algorithm reconstructs the gradient before watershed segmentation; based on the reconstruction, a floating-point active image is introduced as the reference image of watershed transformation. "Floating point" means that the image data float. Floating-point active image has comparatively high light data near the boundary point of the article, and there are comparatively low and even light data inside of the article. Therefore, the floating-point active image reflects the rough contour information of the article. Finally, a graph theory-based algorithm Grab Cut is used for fine segmentation [8]. The whole framework can be seen in Fig. 5

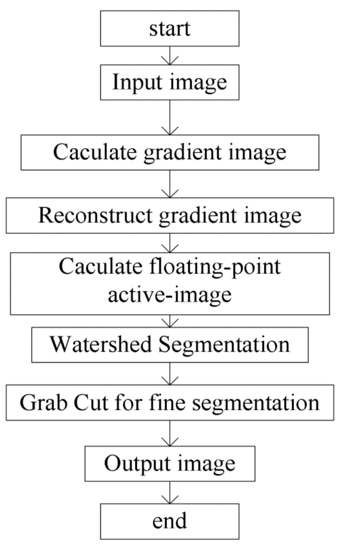

Fig. 5. Framework of the Hybrid Watershed-GrabCut algorithm [8]

In the proposed framework, the image's gradient has been fed into the watershed algorithm for better performance and to reduce the over-segmentation problem. Then, for even finer tuning of the segmentation, Grab Cut has been utilized. Thus, we can say that watershed segmentation has been used for superpixel formation while keeping the image's main contextual features intact. By forming so-called superpixels, the Grab Cut algorithm can be faster and, if done right, more reliable segmentation. This is because if superpixels are able to preserve the contextual features such as the size and shape of a small tissue, we can consider Grab Cut to have prior for segmentation which increases the reliable segmentation.

In this method, the gradient image is reconstructed by morphological mixed opening and closing reconstruction operation. Opening removes small objects from the foreground (usually taken as the bright pixels) of an image, placing them in the background, while closing removes small holes in the foreground, changing small islands of background into foreground [9]. This operation can eliminate regional extremum in gradient images caused by irregular gray-scale disturbance and noise and retains extremum information of essential contours [8].

As for Grab Cut segmentation, each pixel is labeled as being in the foreground or the background of the image [10]. The user draws a rectangle around the region of interest and defines the region outside the rectangle as "Sure Background." Then, the Gaussian mixture model (GMM) has been implemented for the background and foreground. Then, the parameters of GMM are learned from finding the argument which minimizes the U Term shown in Fig. 6.

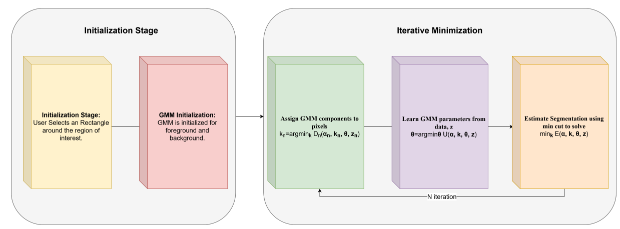

Fig. 6. Framework of the GrabCut algorithm

The results of this proposed framework is shown in Fig. 7.

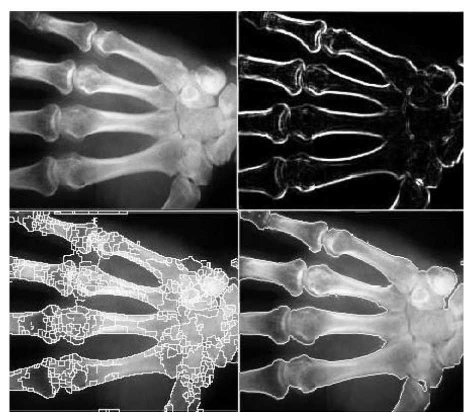

Fig. 7. Results of the Hybrid Watershed and Graph Cut Segmentation [8]

B. Hybrid Watershed and K-means Clustering Segmentation

Similar to the previous method, one group also wanted to utilize the power of the watershed algorithm since the use of the conventional watershed algorithm for medical image analysis is widespread due to always being able to produce a complete division of the image. However, unlike the previous work, to reduce over-segmentation, they have introduced K-means clustering [11].

The main framework can be seen in Fig. 8. It has been observed that there are many regions with similar intensities in a medical image, which result in many local minima that increase over-segmentation of watershed algorithm. Thus, K-means clustering is applied first in order to eliminate excess local minima [11]. Then, similar to previous works, gradients of this new image are calculated and passed into the watershed algorithm. Unlike previous works, automated thresholding technique has been utilized, which is based on the histogram of the normalized gradient magnitude [11]. All edge map pixels with values greater then the threshold retains its original values while those edge map pixels with values less than the threshold had their values set to zero.

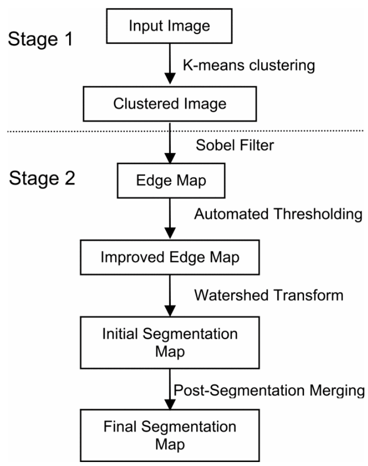

Fig. 8. Framework for the Hybrid Watershed and K-means Clustering Segmentation [11]

The result of the hybrid K-means clustering and watershed algorithm can be seen in Fig. 9.

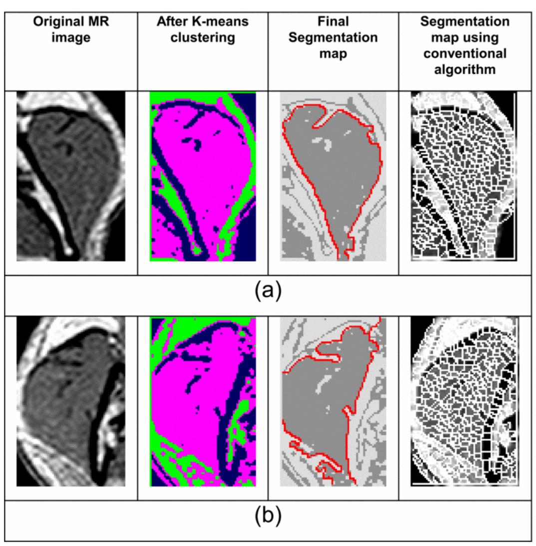

Fig. 9. Result for the Hybrid Watershed and K-means Clustering Segmentation [11]

C. Hybrid K-means Clustering and Graph Cut Segmentation

Like Hybrid Watershed and Graph Cut Segmentation algorithm, K-means clustering and Graph Cut hybrid algorithm have also been proposed. Similarly, in this hybrid method, K-means has been used as a superpixel formulation method that is then passed onto the graph cut algorithm [12]. One of the advantages of the clustering method for preprocessing is that it has significantly lesser computation cost while also being able to cluster features in an image better than the original watershed algorithm [13].

As for the Graph Cut algorithm, the technique partitions the image into two regions where the extracted object region holds the original pixel value and the background region is entirely black. The image is represented in a graphical form such that the vertices represent the pixel location and the edges represent the thickness between neighboring pixels. If the edges have lower thickness this means there is a lower similarity between the adjacent pixels subsequently cut is performed. The energy function is responsible for the optimum cut in the regional and boundary term graph. The main idea of the graph cut algorithm can be seen in Fig.10.

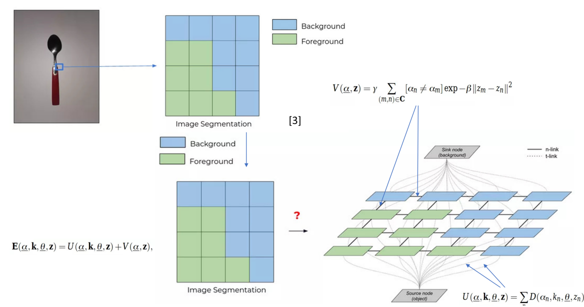

Fig. 10. The Graph Cut Algorithm [14]

The regional term is measured to calculate the penalties for tagging a pixel as a background or object. Various parameters can be chosen to partition the graph. Generally, Gaussian Mixture Model (GMM) has been utilized for the Graph Cut method [10].

Graph Cut takes advantage of the graph-like structure of an image to obtain the segmentation. Each pixel has the following:

- One "n-link" to each of its 4 direct neighbors
- Two "t-link" to the source and sink nodes of the graph, representing respectively the image foreground and background, which can be seen in Fig.10.

After graph construction, the image segmentation task consists of finding the cut of the minimal cost that separates foreground and background. The calculation of the minimal cost is done through "Gibbs" energy of the form:

$$E(\alpha, \theta, z) = U(\alpha, \theta, z) + V(\alpha, z) \tag{1}$$

where the term U evaluates, the fit of the opacity distribution α and V is the smoothness term. θ represents the parameters of GMMs, and z is the array of image pixels. Once the iterative loop finishes, labels around the segmentation border are refined and classified as sure background, probable background, probable foreground, and sure foreground.

The framework for the hybrid model of K-means with Graph Cut is given in Fig. 11. Firstly, the input image is first converted into a grayscale image. Then, the image is passed onto the K-means algorithm to obtain effective centroid segmentation points. Then, after the preprocessing step, the new image is passed into the Graph Cut algorithm.

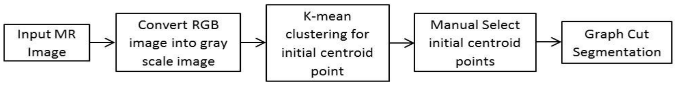

Fig. 11. The Hybrid kMean-Graph Cut Algorithm [12]

In a way, one can consider K-means for creating superpixel. However, this is only an intuitive observation. In reality, the K value is usually chosen to be around 10, which is significantly low to be considered as a superpixel [12]. Nonetheless, with K-means, noise in the medical image has been reduced, and also similar features are grouped together, which enables the graph cut algorithm to have prior knowledge about the features in a medical image. The result of this hybrid algorithm can be seen in Fig.12.

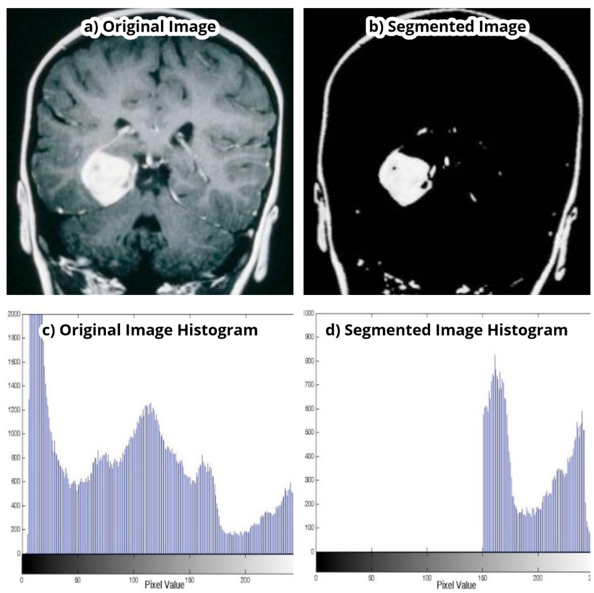

Fig. 12. The Result of Hybrid kMean-Graph Cut Algorithm [12]

The k-means graph cut segmentation technique effectively extracts the ROI, as observed in Fig.12. This extraction gives the tumor a clear perceptibility irrespective of the type, shape, and location. The histogram of the method also shows a lower number of pixels present in the segmented region, implying better and more effective extraction. Thus, it can be said that the proposed k-mean clustering with graph cut segmentation technique is an effective way to segment the tumor of any irregular shape and can be effectively used in medical image applications.

IV. Discussion & Conclusion

In this method, we have briefly described the existing classic segmentation methods with their advantages and disadvantages. We also present the hybrid segmentation methods in detail, which can still be helpful for in the era of deep learning. Due to many different segmentation methods, which will confuse the research direction, we have classified these methods into five main directions. They are threshold-based, edge-based, region-based, watershed-based, and energy-based segmentation methods. After this classification, researchers can put weight on different aspects as their requirement. However, as seen in this method, it is not necessary for the five kinds of segmentation methods to be executed independently. Most of the time, they can be combined to improve the segmentation result.

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