Image Segmentation Techniques using Intelligent Scissors: A Review

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***Abstract*—Within many computer vision applications, image segmentation techniques have been the focus for a lot of disciplines. Several automatic and semi-automatic algorithms for extracting objects from images have been developed. Semi-automatic methods of image segmentation have proven to be the most efficient and reliable, especially for medical applications. Intelligent Scissoring is a technique that uses the input from a user as a guidance for proper segmentation of images using automatic algorithms. However, this method has many issues and weaknesses. Therefore, researchers have been developing different variants of Intelligent Scissors which improve results and reduce the user interaction required. This review presents an overview of the latest methods and algorithms regarding semi-automatic segmentation, and even expanding onto 3D semi-automatic image segmentation.**

Keywords—review, image segmentation, intelligent scissors, semi-automatic, medical image segmentation, 3D segmentation, object extraction.

I. Introduction

In regular Intelligent Scissors, pixels in an image are transformed into a graph of weights assigned to each pixel that are calculated using a cost function. Then, the user selects a suitable starting point on the boundary of the object to be extracted. As the user moves the mouse across the boundary, the shortest path following the mouse will be calculated using Dijkstra's algorithm then displayed.

When the user places the next seed point the previous path gets fixed and the next path initializes. Until the object contour is completed. The issue with this method is that it uses the intensity gradient in its calculation. If the image is highly textured, this method fails to provide good results unless many more seeds are used. Also, this method is poor when dealing with images of low quality, low contrast, non-uniformity or noise.

Methods developed upon Intelligent Scissors vary a lot in terms of purpose, technique, application, computational requirement, dimension space, etc. This review presents the major methods developed from Intelligent Scissors. Part II presents 2D segmentation methods. Part III will have 3D segmentation techniques. Part IV will give a brief conclusion while Part V will be future work.

II. 2D Intelligent Scissors Methods:

A. IT-Snaps:

It is a new image segmentation method similar to image scissoring but is reliant on the texture of an image[1]. It is called interactive texture snapping system (IT-SNAPS). It is an interactive segmenting method that takes input from the user on the fly. This method has been introduced because regular Intelligent Scissors and its variants could not appropriately segment complex images.The user is constrained to operate on image based properties in order to produce accurate segmentation results.

IT-SNAPS, will be formulated using two-texture segmentation problems. Depending on which texture is dominant within the current region of segmentation, the weights assigned to one of each texture would be greater than of the other. Once the user moves into another region of different textures the weight will change accordingly.

Consider the general problem of segmenting an image from a heterogeneous background which is made up of K distinct regions of different textures. We describe each of those regions by a combination of N features. Then, we represent each region by a mix of these features weighted by factors to each feature. This way we dichotomize the two regions along a certain segment of the contour in order to segment the image.

The calculation of these weights when segmenting along any certain part of the image is done so that the weighted sum of feature gradients along the points of the path is maximized. After we find the optimal mixing of weighted features, the algorithm will complete the formulation of the boundary along that part of the image. The user has to employ different pairs of seeds each time the textures along a path change from previous ones.This method is superior to regular IntelligentScissors with regard to its accuracy and user-friendliness. See Fig.1.

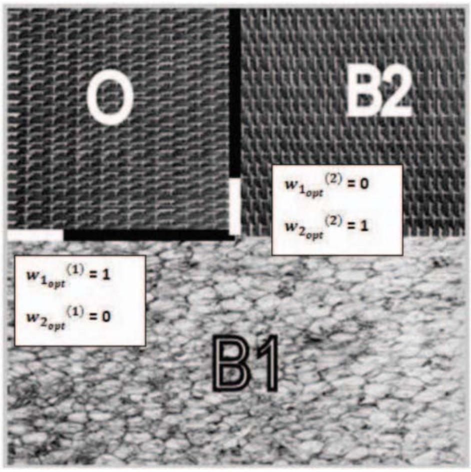

Figure 1: Image segmentation using IT-SNAPS technique

B. Enhanced Intelligent Scissors:

Enhanced Intelligent Scissors is a method proposed in order to resolve issues related to segmentation of medical images using regular Intelligent Scissors [2]. This method relies upon a solid complex wavelet phase-based model as an external proximate value that is invariant to non-uniformities within the image, contrast and noisy images, typically found in medical images. The boundary of images is extracted using Hidden Markov Model. Then, the optimal boundary isfound using a second order Viterbi algorithm. Experiments using this method achieved very accurate segmentation in medical images with less user interaction compared to Intelligent Scissors.In this improved Intelligent Scissors method, the expert picks a starting value on the perimeter of the object to be segmented as with the regular Intelligent Scissors method. Butthe expert picks a sequence of values around the contour without following it closely. Next, a boundary gets formed between these points around the region of interest using the algorithm. See Fig.2.

1) External local cost extraction:

First, the starting approximation of the nearby phase coherence of the picture is acquired. As the next iteration starts, nearby phasesarereevaluated using the last iteration's phase values. Using this result, a revised approximation of the picture is evaluated again from moment adaptive estimation method. This new representation of the image provides a new estimate of the phase values in order to start the next iteration.Benefits of estimation via the phase representation in external value are as follows. First, it makes the extraction not affected by contrast and non-uniformities found in medical imagery. Second, it makes it robust against signal noise.

2) Hidden Markov Model of Boundary Extraction:

Our next step is to shape out the boundary formulation model from the inexact points inputted by the user. First, a curve is fitted between any two input points. Then, q normals are evaluated on the points of that curve. Each of those orthogonalsis considered by p nodes, giving a total of pq nodes. The hidden states of the Hidden Markov Model (HMM)areformulated by the points running on the boundary orthogonals. Solving the HMM can be found in a very efficient way using Viterbi algorithm.

3) Second Order Viterbi Boundary Optimization:

The final step is to solve the HMM formulation of the boundary contour. While the Viterbi method is highly efficient, sometimes it can become slow due to a large number of states within the HMM. In order to make sure that the computational requirement of solving the HMM does not become too great, we have to introduce a global threshold that is adaptive based on the extracted moment of coherence.

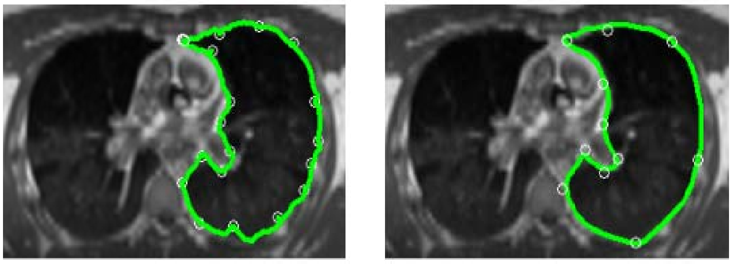

Figure 2: Medical image segmentation using Enhanced Intelligent Scissors

C. Growing Region and Level Sets Technique:

This method is based on the local features of an image. It relies on two main concepts [3]. First is the intensity invariance of phase local information which is useful in low grade MR images of brain tumors. The second part is the level set technique formulated in combination with expanding region in order to improve segmentation of brain tumors. One type of brain tumors is the low grade gliomas (LGG) which is more difficult to detect than other types oftumors. That is due to itsvarying type, place and nature from one condition to another. Typical methods of segmentation rely on a formulation of intensity gradient which is not suitable for LGG detection. This approach will combine the level set method with the growing region relying on the proximate phase knowledge.

1) Level Set Function:

This is a contour information method. First step is to start the level set function (LSF) from combining the growing region with the morphological mathematical operation making a quality binary mask. Next is to evolve the LSF function depending on a number ofreruns of the algorithm by means of the starting contours from the step before.

2) Local Phase Information:

The method of local phase information is reliant of the concept of symmetry. Symmetry helps in detecting the edge of an object. We identify symmetry and asymmetry points using a frequency based approach where the local phase reaches the maximum.The proximate phase knowledge is evaluated from filters such as quadrature filters including even and odd bandpass filters. Then, the local phase information is reliant on the combination of different scales of N-D signals. The local phase is estimated from 1-D signals using the combination of the original signal with the Hilbert transform. Moreover, the local phase information is also estimated from an N-D signal using Felsberg and Sommer signal based on Riesz transform.Kovesi proposed a method of finding Feature Asymmetry (FA) measure via the local phase information. This method relies on the odd and even filters proposed above.

3) Level Set Method:

Due to the complexity of LGG’s structure, the level set method is most suitable technique for our work. The basic idea is to build a mathematical formula as a zero function of a higher function labeled as a signed distance. The result constitutes the level set function.In results, the general contour around the tumor is found correctly. Comparing with the gradient intensity method, contours resulting from this method are relatively close to manually segmentations made by experts.This method has helped develop a better way of initializing the contour detection which constitute the main contribution of this method. See Fig.3.

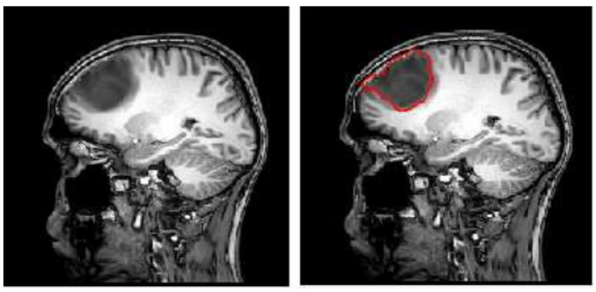

Figure 3: Segmentation using Growing Region and Level Sets Technique.

D. Power Watersheds

In this study, we comprise a method of seeded image segmentation that includes graph cuts, random walker, shortest path optimization and watershed methods all together [4]. We express our algorithm in terms of a common energy function whose parameter is an exponential of the difference between collection of nodes within a local region. We call this method power watersheds.

1) Watersheds:

The gradient of the image is treated as the relief map. Then, a seed is inputted from the user in order to start the segmentation of image into different proper separate objects. A minimum expansion forest algorithm evaluates trees extending all the main points of the graph. Each tree is related to exactly one seed input by user and the cost assigned to the group of trees getsminimized.

2) Graph cuts:

The graph cuts algorithm produces the contour around objects by finding the minimum values between a foreground and background user input main seeds using a maximum change computations.

3) Random walker:

The random walker of Grady is formulated using a weighted graph. It defines labels for unseeded nodes by assigning pixels to the most likely seed that sends a random walker. In other terms, assigning unlabeled pixels to seeds that have a minimum diffusion distance.

4) Shortest paths:

The algorithm of shortest paths assigns pixels to the object of interest if there is a closer path from that point to main point within the same object of interest than to any other irrelevant seeds. Paths are weighted by image content.

5) Broadening the framework of watersheds:

In image processing applications, each pixel is related to a node. Node are connected to their proximate 4 or 8-point lattice. A cost evaluated graph gives values to the perimeters. Affinity weights are also added to penalize the affinity of foreground or background at a single node. Nodes that are strongly connected will have high weight while weakly connected nodes will have small weight. Within this methoddifferent combinations of the five methods were tested: random walker, graph cuts, watersheds/maximum spanning forest shortest path, and power watersheds.We proposed a general framework encompassing all of these methods which in turn might provide value whenever any of them improves. This framework defines a new family of algorithms of optimal extending forest method. This produced the power watershed method using exponents. See Fig.4.

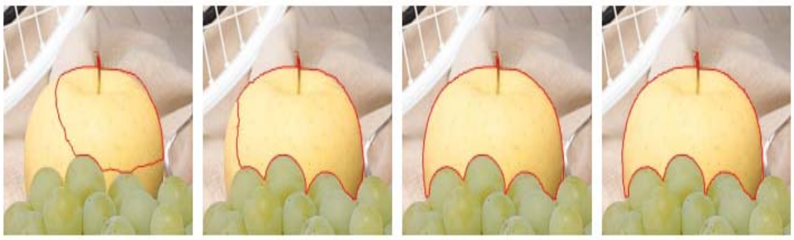

Figure 4: Image segmentation using power watersheds.

E. AntSeg: Ant Colony Optimization to Interactive Image Segmentation:

This method develops a combination of the artificial ant behavior and the image gradient segmentation technique [5]. Artificial ant colony behavior is based on the way ants take as they go out of their homes. They leave behind on their tracks a trace of a pheromone. This substance is then traced by other ants. When the ants reach to their target, they strengthen the path with depositing more substance on thesame path. Moreover, irrelevant paths with less substance deposited on them disappear as the pheromonesdisappear after some time. This way only the shortest path stays and longer paths disappear.More refinement of this method is done by use of heuristics in order to find best results. This kind of method is not deterministic: same input does not always lead to the same output. See Fig.5.

1) Interactive Image Segmentation:

Usually, we compute the gradient of an image in order to observe the edges of objects within it. For our algorithm, we use the weighted gradient operator. It is a gradient for color images. Transforming an image into the HIS space model of colors, this gradient consists of the combining the cost gradients from the color bands of the image, linearly. The more importantthe knowledge within a single band, the more weight will be assigned to its gradient.

2) Artificial Ant Colonies:

To construct the contour of segmentation, we begin with two vertex and a minimum path connecting them. Each artificial ant constructs a static and connected graph using some heuristic information and the trace of pheromones left by previous ants. The combination of all graphs made by the ants will give the best solution.

3) AntSeg:

Ants look for a suitable path by using the morphological gradient and the provided heuristic knowledge. The enhanced borders from the image gradient are the weights assigned to the pheromones.The user provides the starting point on the image. The next mouse click is the next destination for the ants. Multiple paths are found between the two points by different unique ants. The best path is compared to the latest solution. The user can set the number of iterations and number of ants of the operation. An objective function is used after each iteration to improve the pheromone trace of the latest solution. It helps minimize the length of the current path. It also assists in finding the heuristic knowledgecollected along that path. All paths built by different ants may be accepted or rejected by the expert. In both cases, pheromone traces along all paths get updated.

4) Decision Rule:

An ant constructs a solution by an incremental choice of path. The decision starts from the initial point to any neighboring point except those that have been visited by other ants. The decision considers pheromone, gradient and distance between start and end points. This way we get the optimal unique solution by each ant.

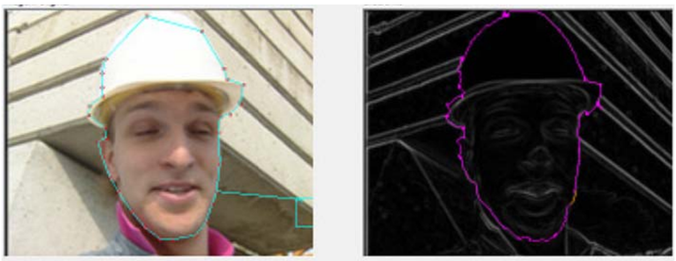

Figure 5: Image segmentation using AntSeg

III. 3D INTELLIGENT SCISSORS METHODS:

A. Multilayer Segmentation Using Gaussian Weighted Euclidean Distance and Nonlinear Interpolation:

Multilayer segmentation is a common approach for reading and diagnosis of MR images[6]. In this method, we propose a new approach for multilayer object extractionformulated from Gaussian Weighted Euclidean Distance then nonlinear interpolation.Results show that segmentation using this method is accurate andtime efficient compared to current semi-automatic segmentation methods.

To begin with, we segment the top and bottom layers using a better developed live-wire method. This technique is the canny edge detector technique. Ideal segmented layers are evaluatedwhen the expert moves mouse pointer from one point to another, a “live-wire” contoursticks to and goes around the object to be segmented. New input of seeds fixes the previous selected segment and starts the next one,until the boundary is completed.

This way, we generate two ideal segmentations of the first and last layers. Then we calculate the Gaussian weighted Euclidean boundaries of these two layers. The next step is normalizing the results. We multiply with the Euclidean Distance of the contour. Thus, we acquire the Gaussian Weighted Euclidean Distance of top and bottom layers of the image. These results will then be regarded as prior knowledge when computing the interpolation of the in-between layers in order to segment them.See Fig.6

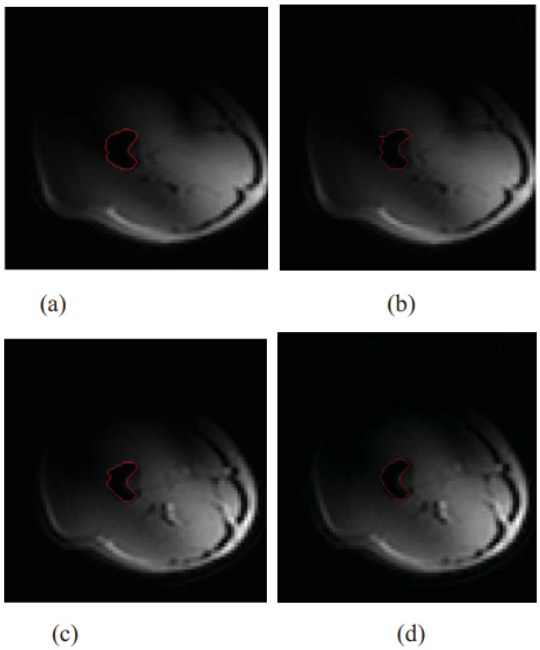

Figure 6: Image segmentation stages using multilayer segmentation technique

1) Improved Live-Wire:

We have developed a more advanced live-wire algorithm to search for the minimum value function along any two seeds in 2D images. This function is comprised of the following terms: gradient magnitude, LoG edge detection, canny edge detection and their weight constants.

2) The Gaussian Weighted Euclidean Distance:

A binary image will represent the contour where the contour pixels will have value of ones and the rest will be zeros. Thus, we will have two binary images for the two layers. Then using city-block transformation, we reformulate those two binary images. We make distances outside and inside the contours negative. After that, we search for cavities to be filled within the binary image compared to the original image. Finally, we find the pixel coordinates that are in the contour by detecting ones and setting positive values to city-block distances only inside the main contour.

3) The Nonlinear Interpolation Function:

Using a nonlinear interpolation that is reliant on Gaussian weighted Euclidean distance. We can interpolate many slices efficiently.Using the new contours for the first and last layers, we can interpolate the data in order to generate segmentation for the layers in between.

B. Improved Live-Wire for 3D Images:

Sometimes, regions of interest within CT images are a little tricky to segment due to having soft-tissue structures and small intensity dynamic range[7]. In this method, we enhanced the live-wire-based image extraction methods of 3D objects in order to improve the results associated with medical CT images. Regions of interest may vary in shape, size and boundary. We can extend the live-wire method to 3D either by processing several sectional images from orthogonal planars or iteratively adjusting boundaries starting from previous segmentation results.

This method relies on the concept of the iterative segmentation and adjustment of boundaries moving from layer to layer. We will introduce control parameters and cost features to harness the knowledge acquired from previous segmentation and improve the new processed image.

1) Iterative live wire:

Many approaches have been developed to extend the live-wire method to 3D. One technique is to consider the 3D segmentation as a collection of 2D segmentations of the original 3D object. Iterative Live-Wire (ILW) uses a selected slice that gets segmented. Then, it projects that slice to the next and previous slice in order to use that information as an initial boundary. Then, several control points are used to separate this initial slice evenly. Those segments will be redefined using live-wire paradigm to produce a new boundary segment that is close to the true boundary on the current image. Different segments will be used iteratively in order to adjust the boundary. When the accumulated cost along the boundary does not change much, the process ends. See Fig.7.

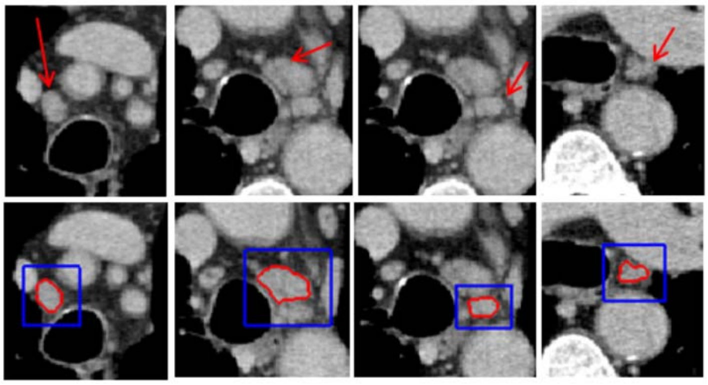

Figure 7: Image segmentation using improved live wire for 3D

IV. CONCLUSION:

Research regarding image segmentation has been developed under many disciplines depending on the specialized kind of task that was required. These methods presented in this review differ in certain ways. They try to reduce user interaction while improving the accuracy of the image segmentation. They also try to deal with bad quality images as well as with noise and low contrast. Some methods moved into the live interactive segmentation since the input of the expert user is quite valuable to produce accurate segmentation and to save time. As for 3D, methods have been developed relying on the 2D methods. 3D images also have many important applications.

V. FUTURE WORK:

Future research regarding Intelligent Scissors techniques should focus on several topics. First, it should focus on reducing the input required to segment complex images. Second, the algorithm should be developed more to accommodate for highly textured images. It should also rely on more feature types extracted from the image and determined by the user. Moreover, the results provided for these methods should be extended for a wider variety of images. Also, 3D semi-automatic image segmentation is quite an essential part of image processing field within medical applications. It also requires more research anddevelopment. Moreover, all semi-automatic methods should display the contour live as it starts to calculate it. This will provide more accuracy. Finally, developing a super method that relies on several different algorithms might be advantageous in the sense that any improvement on these algorithms will provide improvement for the super method.

REFERENCES

[1] Gururajan, A., Sari-Sarraf, H. & Hequet, E. Interactive texture segmentation via IT-SNAPS. 2010 IEEE Southwest Symposium on Image Analysis & Interpretation (SSIAI)(2010). doi:10.1109/ssiai.2010.5483900

[2] Mishra, A., Wong, A., Zhang, W., Clausi, D. & Fieguth, P. Improved interactive medical image segmentation using Enhanced Intelligent Scissors (EIS). 2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society(2008). doi:10.1109/iembs.2008.4649855

[3] Rahima, Z., Ahror, B., Basel, S., Douraied, B. S. & Souhil, T. Segmentation of low-grade gliomas based on the growing region and level sets techniques. 2018 4th International Conference on Advanced Technologies for Signal and Image Processing (ATSIP)(2018). doi:10.1109/atsip.2018.8364479

[4] Couprie, C., Grady, L., Najman, L. & Talbot, H. Power watersheds: A new image segmentation framework extending graph cuts, random walker and optimal spanning forest. 2009 IEEE 12th International Conference on Computer Vision(2009). doi:10.1109/iccv.2009.5459284

[5] Versuti, T. A. B., Flores, F. C., Mulati, M. H. & Polidorio, A. M. AntSeg: The Application of Ant Colony Optimization to Interactive Image Segmentation. 2012 31st International Conference of the Chilean Computer Science Society(2012). doi:10.1109/sccc.2012.20

[6] Zhang, J., Cui, Y., Lu, S. & Xiao, L. Multilayer image segmentation based on Gaussian weighted Euclidean distance and nonlinear interpolation. 2017 10th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI)(2017). doi:10.1109/cisp-bmei.2017.8302195

[7] Lu, K., Xue, Z. & Wong, S. T. A robust semi-automatic approach for ROI segmentation in 3D CT images. 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)(2013). doi:10.1109/embc.2013.6610700