

MICROARRAY IMAGE SEGMENTATION USING IMPROVED GOGAC METHOD

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ABSTRACT

Image Analysis remains one of the major challenges in image Processing. Numerous segmentation algorithms have been developed for a variety of applications. Disappointing outcome has been stumble upon in some cases, for several existing segmentation methods. In this paper, we improved Performance of the Globally Optimal Geodesic Active Contours method for image segmentation application by applying post processing with the results obtained by the GOGAC.

Analysis done using standard images (i.e. The Stanford Microarray Database human peripheral blood mononuclear cells), our concluding segmentation results compare constructively with the results obtained by the GOGAC and Improved GOGAC method. The qualitative analysis done proved that the proposed methods are less perceptible with respect to noise. As such, the rate of in proper segmentation, pixel loss and trapped center at local minima problems can be avoided.

In proposed method, we show that on the image, Improved GOGAC performs better than GOGAC, by correctly predicting the pixels and it is much faster than Active Contours method.

KEYWORDS: Active Contours, Image Analysis, Image Processing, Improved GOGAC, Globally Optimal Geodesic Active Contours

INTRODUCTION

Image segmentation has long been accepted as a complicated setback. A lot of programmed algorithms have been anticipated. In this progression a current prominent development is the Globally Optimal Geodesic Active Contour (GOGAC) [1]. Recently, Incorrect Segmentation results for microarray images have attracted much attention due to their inability of generating correctly segmented spots.

Consequently, using GOGAC for the segmentation of microarray image will affect next step of the microarray data analysis i.e. quantification and analysis (figure 1) [4]. For this reason, this paper presents a robust Improved GOGAC segmentation method that is based on the deformable models. We have compared results of Improved GOGAC with standard GOGAC segmentation method.

In this paper, section 2 briefly introduces GOGAC segmentation methods. Section 3 describes the Improved GOGAC Segmentation technique. Section4 presents the experimental results and conclusions are presented in Sections5.

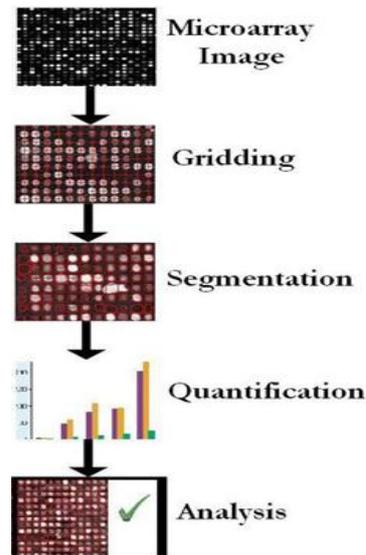


Figure 1: Steps of Microarray Image Analysis Process

GOGAC SEGMENTATION METHOD

Information extraction and segmentation is the major foundation progression of image analysis. One microarray image can have thousands of spots and spots can vary in size, shape, intensity. The spots have to be quantified for further analysis [7]. Effortless closed curve of minimal energy represented through a metric, under the constraint to the geodesic must hold a particular internal point is produced by GOGAC. This limitation is a natural constraint to find a non-trivial global minimum and is also a natural alternative to different adhoc forces that put off contours from collapsing upon themselves. GOGAC is extremely appropriate for automated applications because it is not restricted to convex or point convex curves and avoids various metrication errors due to the image grid with its simple initialization and lack of parameters. GOGAC method has been applied to the segmentation of cDNA microarray images because of these reasons GOGAC performs serial segmentation and produces a closed contour of optimal integrated edge strength. It creates a quality measure and also works on each spot independently. The consequential contours have been shown to be isotropic and exhibit robustness to gaps in object boundaries as well as low sensitivity to the assignment of the interior point. This approach compares quite favorably with the classic curve evolution approach of Caselles [5], accomplishing more reliable and accurate segmentation with reduced computational effort and its fast and efficient.

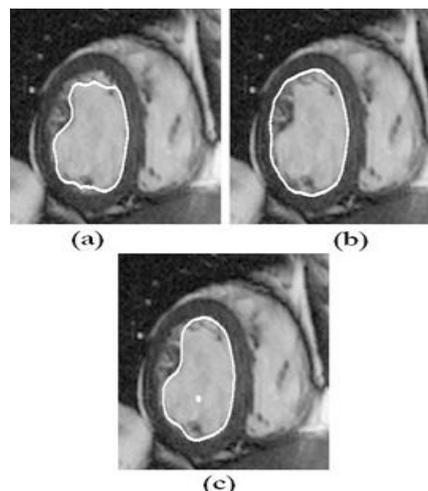


Figure 2: Classic GAC Segmentation (Narrow-Band, Explicit Time Step): 21.5 Seconds
(b) Multiscale GAC Segmentation (Narrow-Band, Implicit Time Step): 3.1 Seconds
(c) Globally Optimal GAC Segmentation: 2.5 Seconds

IMPROVED GOGAC SEGMENTATION METHOD

We have developed an approach to image segmentation based on deformable models to overcome incorrect spot segmentation of microarray images. In particular our method corrects segmentation errors of GOGAC. Our goal is to find ‘under segmented’ spots in the result of GOGAC and improve it by border expansion method. We have used the Globally Optimal Geodesic Active Contours based segmentation algorithm proposed in [1] which is implemented in Spot software [8]. Spot software is available as a package for the free data analysis environment, "R". It uses imview for graphical representation of image Spot initially finds out grid locations (internal point of spots) semi-automatically and afterward Globally Optimal Geodesic Active Contours method generates segmentation results. Spot software quantifies shape of spots, area, perimeter, and circularity and the log ratios of the red and green channels based on median values mean of foreground for each channel and background, interquartile range of foreground for each channel and background are some important features that can be calculated. We have found that GOGAC generates incorrect segmentation (figure3) [7] these types of incorrect spots are corrected by our proposed Improved GOGAC Segmentation method.

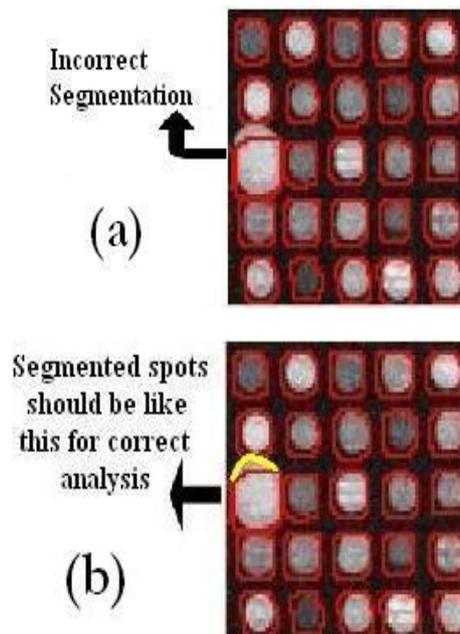


Figure 3: (a) Sample Image of Incorrect Segmentation by GOGAC Method through the Spot Software (b) Sample Image of Correct Segmentation of Spot

In order to quantify and analyze the patterns of spots, method must be able to recognize these spots as being distinct from other normal spots in the image. The procedure used to identify incorrectly segmented spots in the image, intensity thresholding, and finally recognition of the actual spots. The output of the system is generated as an overlay which can be placed onto an image of the complete image sample. The thresholding is performed on the image that selects an optimum threshold value by choosing the pixel intensity from the image's histogram that exhibits the maximum entropy over the entire image. The later stages of the algorithm involve constraints for the identification of unassigned pixels to the spots. This is done by subtracting the image from segmented image of GOGAC result. Finally, the most complex part of the method allows the local border expansion technique to actually make changes in the GOGAC results in order to generate final result of the Improved GOGAC segmentation method. Since almost all image segmentation methods contain parameters that are used to control the segmentation results, our method does not require any parameters other than parameters for GOGAC. Our method can be used for different imaging conditions without any need of parameter tuning. This is an advantage of Improved GOGAC.

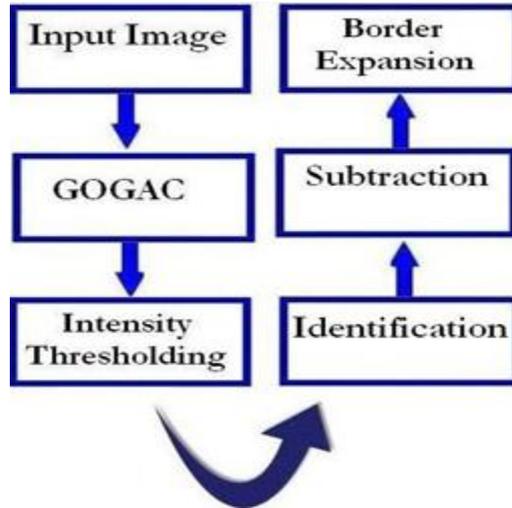


Figure 4: Stages of the Improved GOGAC Method

EXPERIMENTAL RESULTS

In this section, we present the experimental results, indicating the different types of spots. The GOGAC experiment results using the deformable model implemented by Appleton *et al.* [1] are also presented for comparison. The sizes of all the test images are given in Table 1. Our Improved GOGAC segmentation results were tested on over 10 images from the microarray database of Stanford University [3]. We have used the human peripheral blood mononuclear cellular images [2].

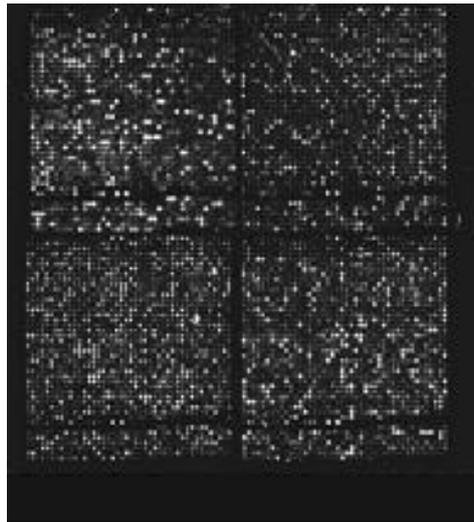


Figure 5: Sample Image from Stanford University

The segmented results are robust in the case of correct segmentation particularly for those spot which pixels are outside the segmented region and, we found these results are very effective for accurate image analysis. Some of the incorrect segmentation is provided in Figures 6(a), 7(a), 8(a), 9(a), 10(a), 11(a) and 12(a). shows a case where the improvement in the spots is needed. In Figures 6(b), 7(b), 8(b), 9(b), 10(b), 11(b) and 12(b) the Improved GOGAC results for images are presented and we can easily observe that results are improved up to more than satisfaction level.

The test examples include five image sets. The results of the first set of examples are shown in Figure 6(a), where we have taken 3×3 spots of GOGAC and compared with the improved GOGAC. The results of the Improved GOGAC method are shown in Figure 6(b).

Table 1: Details of Images Used in the Project

S. N.	Experiment ID	Image Dimensions	No of Blocks (12 Rows with 4 Blocks Each)	Spots per Block
1.	57536	1892x5500	48 blocks	30x30
2.	57537	1948x5601	48 blocks	30x30
3.	57540	1948x5601	48 blocks	30x30
4.	57541	1948x5601	48 blocks	30x30
5.	57538	1892x5500	48 blocks	30x30
6.	57539	1892x5500	48 blocks	30x30
7.	57542	1948x5601	48 blocks	30x30
8.	57543	1948x5601	48 blocks	30x30
9.	57546	1892x5500	48 blocks	30x30
10.	57547	1948x5601	48 blocks	30x30



Figure 6: The Comparison of GOGAC with Improved GOGAC Method. (a) GOGAC Result for 3x3 Spots (b) Improved GOGAC Result for 3x3 Spots, which is Better in Spots whose Pixels are Outside the Boundary than the Other Deformable Model Based Segmentation

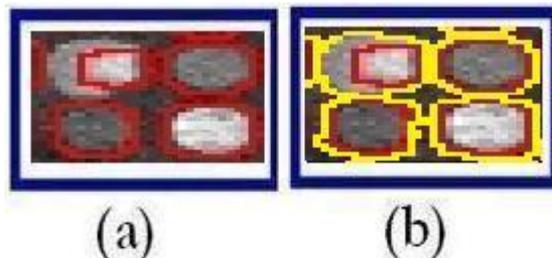


Figure 7: (a) GOGAC Result for 2x2 Spots (b) Improved GOGAC Result for 2x2 Spots

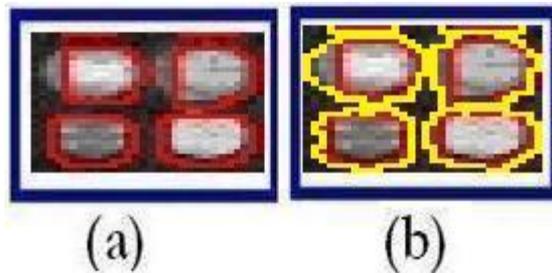


Figure 8: (a) GOGAC Result for 2x2 Spots from View1 (b) Improved GOGAC Result for 2x2 Spots



Figure 9: (a) GOGAC Result for 2 Spots (b) Improved GOGAC Result for 2 Spots

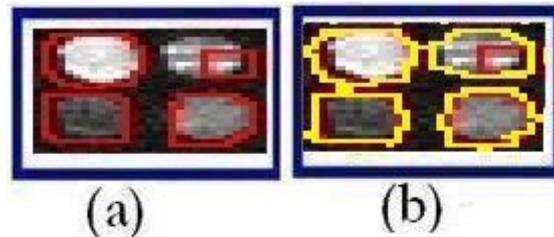


Figure 10: (a) GOGAC Result for 2x2 Spots from View2 (b) Improved GOGAC Result for 2x2 Spots

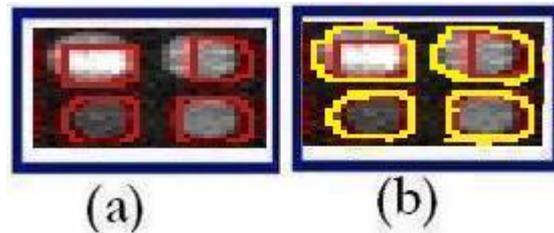


Figure 11: (a) GOGAC Result for 2x2 Spots from View3 (b) Improved GOGAC Result for 2x2 Spots

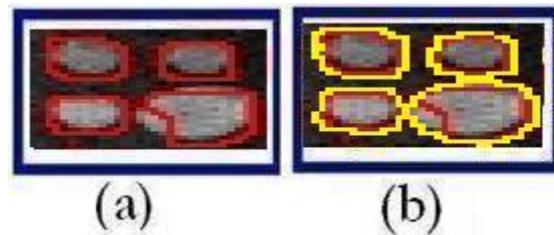


Figure 12: (a) GOGAC Result for 2x2 Spots from View4 (b) Improved GOGAC Result for 2x2 Spots

CONCLUSIONS

The GOGAC segmentation method based on deformable model can be applied to medical image analysis processes. But improper segmentation is major problem. In this paper, an improved method with identification of unassigned pixels, assignment of unassigned pixels to the correct spot by border expansion approach is proposed to overcome the problem. The segmentation to microarray images is effective. Experiment results show that our algorithm provides better results than other deformable models. The proposed algorithm might be a better algorithm for microarray image segmentation with better performance and less time consumes.

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