



Edge Detection using Mathematical Morphology for Gridding of Microarray Image

J.Harikiran*, Raghu Andey, K.Nanditha Krishna,
Dr.P.V.Lakshmi
GITAM Institute of Technology, GITAM University,
Visakhapatnam
jhari.kiran@gmail.com

Dr. ReddiKiranKumar
Krishna University,
Machilipatnam, India

Abstract: A Deoxyribonucleic Acid (DNA) microarray is a collection of microscopic DNA spots attached to a solid surface, such as glass, plastic or silicon chip forming an array. The DNA microarray image analysis includes three tasks: gridding, segmentation and intensity extraction. The size and shape of the spots is different from each other and some spots have low density to make them very difficult to detect, generating errors in processing the microarray images. In this paper, we present a method to eliminate such obstacles by sensing their edges using mathematical morphology. Application of edge detection technology on separating spots from the background decreases the probability errors and gives more accurate information about the status of the spots. After the guided spots are found, the correct grid can be generated. The proposed method is compared with some existing edge detection methods. The experimental results show that the proposed algorithm has found the edges of spots of microarray image more accurately.

Keywords: Microarray, Image Processing, Edge detection, Mathematical Morphology.

I. INTRODUCTION

Microarrays, widely recognized as the next revolution in molecular biology, enable scientists to analyze genes, proteins and other biological molecules on a genomic scale [1]. A microarray is a collection of spots containing DNA deposited on the solid surface of glass slide. Each of the spot contains multiple copies of single DNA sequence [2].

Microarray expression technology helps in the monitoring of gene expression for tens and thousands of genes in parallel. During the biological experiment, the mRNA of two biological tissues of interest is extracted and purified. Each of the mRNA samples are reverse transcribed into complementary DNA (cDNA) copy and labeled with two different fluorescent dyes resulting in two fluorescence-tagged cDNA (red Cy5 and green Cy3). The tagged cDNA copies, called the sample probe, are hybridized with the slide's DNA spots. The hybridized glass slides are fluorescently scanned at different wavelengths (corresponding to the different dyes used), and two digital images are produced, one for each population of mRNA.

Each digital image contains a number of spots of various fluorescence intensities. The intensity of each spot is proportional to the hybridization level of the cDNAs and the DNA dots, the gene expression information is obtained by analyzing the digital images [3][4].

The processing of the microarray images usually consists of the following three steps: (i) gridding, which is the process of assigning the location of each spot in the image. (ii) Segmentation, which is the process of grouping the pixels with similar features and (iii) Intensity extraction, which calculates red and green foreground intensity pairs and background intensities.

During processing of microarray images, irregularities of spot position and shape could generate significant errors: small regions of signal spots can be mis-included into background area and vice versa [5]. We can eliminate such obstacles by sensing the edges of the spots. In this paper we present an edge detection method using mathematical

morphology. Application of edge detection technology on separating spots from the background identifies the location

of good quality spots [6]. A good quality spot should be circular in shape, with intensity consistently higher than the background. After the good quality spots are found, the correct grid can be generated. Based on the spot edges, a refinement procedure follows which further improves the existing grid structure, by slightly rotating or transposing the line-segments.

This paper is organized as follows: Section II presents Mathematical Morphological operations, Section III presents, Edge Detection of Microarray image using Mathematical Morphology, Section IV presents Experimental results, and finally Section V reports conclusion.

II. MATHEMATICAL MORPHOLOGY

In morphology, basic operations include erosion, dilation, opening and closing [7].

The erosion of an image I by a flat structuring element b at any location (x,y) is defined as the minimum value of the image in the region coincident with b when the origin of b is at (x,y) . In equation form, the erosion at (x,y) of an image I by a structuring element b is given by

$$[I \ominus b](x,y) = \min_{(s,t) \in b} \{I(x+s, y+t)\} \quad (1)$$

The dilation of an image I by a flat structuring element b at any location (x,y) is defined as the maximum value of the image in the window outlined by $\hat{b}$ when the origin of $\hat{b}$ is at (x,y) . In equation form, the erosion at (x,y) of an image I by a structuring element b is given by

$$[I \oplus b](x,y) = \max_{(s,t) \in b} \{I(x-s, y-t)\} \quad (2)$$

The opening of image I by structuring element b , denoted $I \circ b$ is

$$I \circ b = (I \ominus b) \oplus b \quad (3)$$

Similarly, the closing of I by b , denoted $I \bullet b$, is

$$I \bullet b = (I \oplus b) \ominus b \quad (4)$$

III. EDGE DETECTION USING ADAPTIVE MULTISTRUCTURE MORPHOLOGICAL ALGORITHM

Because of the unicity and fixity of SE in traditional Edge detection using mathematical morphology, there are two main deficiencies [8]: on the one hand a single SE can only detect the edge of the same direction with the SE, but is not sensitive to different directions; on the other hand large-scale SE has strong ability to restrain noise, but the detected edge image is rough, small-scale SE is good at checking the details of the edge, but weak at noise suppression. In order to effectively restrain noise and preserve image edge information, we use multi-structure morphological adaptive algorithm to get the edge images.

We calculate the gray scale distance of original image to adaptively define the weights of SEs.

The eight structuring elements of different directions with the size of 5X5 are shown in figure 1.

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Figure 1. SEs with different directions.

a ₉	a ₈	a ₇	a ₆	a ₅
a ₁₀	a ₂₃	a ₂₄	a ₂₅	a ₄
a ₁₁	a ₂₂	a ₁	a ₂	a ₃
a ₁₂	a ₂₁	a ₂₀	a ₁₉	a ₁₈
a ₁₃	a ₁₄	a ₁₅	a ₁₆	a ₁₇

Figure 2. Image Sub-block

Figure 2 shows the sub-block with the size 5X5, in which a₁ is the gray-scale value of the center pixel, and a₂,a₃,a₄,...,a₂₅ stand for its neighborhood gray scale value, then the gray-scale distance of a₁ and its neighborhood can be performed as:

$$d_k = |a_1 - a_k|, k = 2, 3, 4, \dots, 25. \quad (5)$$

The larger the gray-scale distance, the higher extent of salutation, and the bigger possibility that the pixel is an edge point in the image. The Edge Gray-Scale distances of a₁ can be defined as follows.

$$G_1(x,y) = d_4 + d_5 + d_6 + d_7 + d_8 + d_9 + d_{10} + d_{12} + d_{13} + d_{14} + d_{15} + d_{16} + d_{17} + d_{18} + d_{19} + d_{20} + d_{21} + d_{23} + d_{24} + d_{25}; \quad \text{---for direction } 0^\circ$$

$$G_2(x,y) = d_4 + d_5 + d_6 + d_7 + d_8 + d_9 + d_{10} + d_{12} + d_{13} + d_{14} + d_{15} + d_{16} + d_{17} + d_{18} + d_{19} + d_{20} + d_{21} + d_{22} + d_{23} + d_{24} + d_{25}; \quad \text{---for direction } 22.5^\circ$$

$$G_3(x,y) = d_2 + d_3 + d_4 + d_6 + d_7 + d_8 + d_9 + d_{10} + d_{11} + d_{12} + d_{14} + d_{15} + d_{16} + d_{17} + d_{18} + d_{19} + d_{20} + d_{22} + d_{23} + d_{24}; \quad \text{---for direction } 45^\circ$$

$$G_4(x,y) = d_2 + d_3 + d_4 + d_5 + d_7 + d_8 + d_9 + d_{10} + d_{11} + d_{12} + d_{13} + d_{14} + d_{15} + d_{16} + d_{17} + d_{18} + d_{19} + d_{21} + d_{22} + d_{23} + d_{24} + d_{25}; \quad \text{---for direction } 67.5^\circ$$

$$G_5(x,y) = d_2 + d_3 + d_4 + d_5 + d_6 + d_8 + d_9 + d_{10} + d_{11} + d_{12} + d_{13} + d_{14} + d_{16} + d_{17} + d_{18} + d_{19} + d_{20} + d_{21} + d_{23} + d_{25}; \quad \text{---for direction } 90^\circ$$

$$G_6(x,y) = d_2 + d_3 + d_4 + d_5 + d_6 + d_7 + d_9 + d_{10} + d_{11} + d_{12} + d_{13} + d_{14} + d_{15} + d_{17} + d_{18} + d_{19} + d_{20} + d_{21} + d_{22} + d_{23} + d_{24} + d_{25}; \quad \text{---for direction } 112.5^\circ$$

$$G_7(x,y) = d_2 + d_3 + d_4 + d_5 + d_6 + d_8 + d_9 + d_{10} + d_{11} + d_{12} + d_{13} + d_{14} + d_{16} + d_{17} + d_{18} + d_{19} + d_{20} + d_{21} + d_{23} + d_{25}; \quad \text{---for direction } 135^\circ$$

$$G_8(x,y) = d_2 + d_3 + d_4 + d_5 + d_6 + d_7 + d_8 + d_{10} + d_{11} + d_{12} + d_{13} + d_{14} + d_{15} + d_{16} + d_{18} + d_{19} + d_{20} + d_{21} + d_{24} + d_{25}; \quad \text{---for direction } 157.5^\circ$$

As for the whole image, the gray-scale distances of each edge and adaptive weights of SEs can be calculated as below:

$$ED_k = \sum_{x=2}^{M-1} \sum_{y=2}^{N-1} G_k(x,y), k=1,2,\dots,8 \quad (6)$$

$$w_k = ED_k / \left(\sum_{k=1}^8 ED_k \right), k=1,2,\dots,8 \quad (7)$$

The edge E extracted adaptively by multi-structure morphology is given by

$$E = \sum_{k=1}^8 w_k [(I \circ b_k) \oplus b_k - (I \cdot b_k) \ominus b_k] \quad (8)$$

IV. EXPERIMENTAL RESULTS

Proposed Spot edge detection mechanism is performed on a sample microarray slide that has 48 blocks, each block consisting of 45 spots. A sample block has been chosen and 45 spots of the block have been cropped for simplicity. The

sample image is a 154*200 pixel image that consists of a total of 54684 pixels. The RGB colored image microarray image have been converted to grayscale image to specify a single intensity value that varies from the darkest (0) to the brightest (255) for each pixel shown in figure 3.

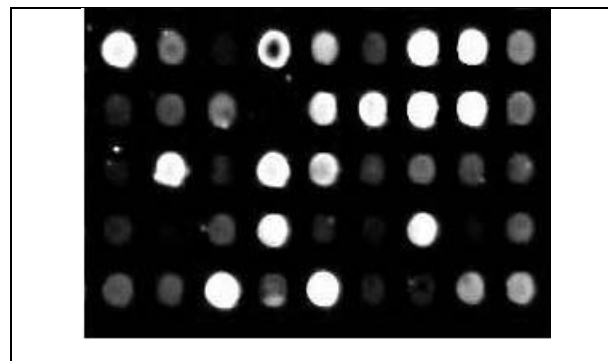
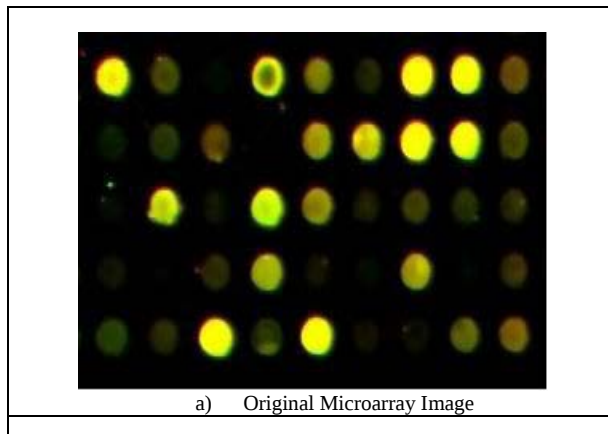
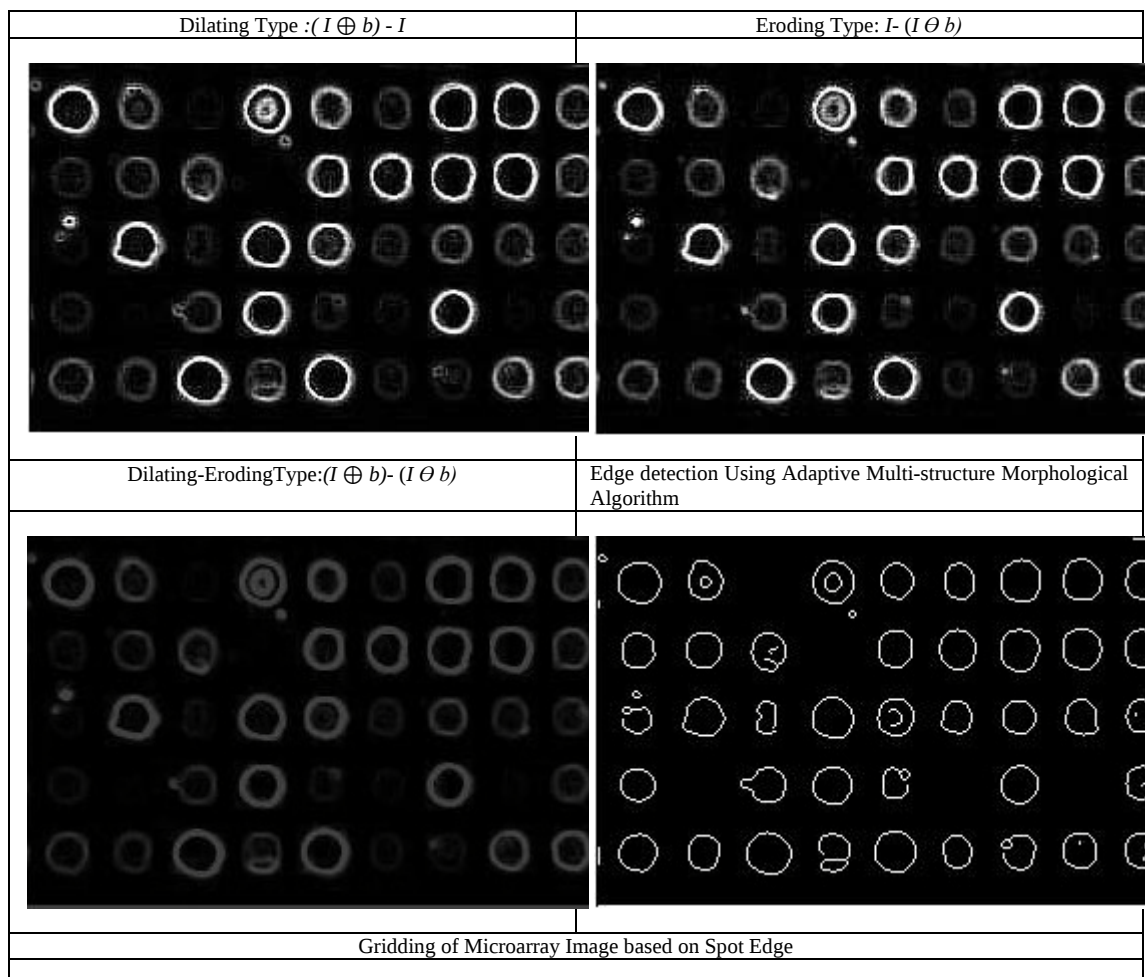


Figure 3 a) RGB Color microarray image b) Grayscale Image

The edge detection results of microarray image are presented in figure 4. The proposed algorithm is compared with existing morphological edge detection operators. The advantage of using our algorithm is that it will not leave even a single weak spot. Performance can be compared by considering the number of edge pixels detected by various methods using mathematical morphology as shown in table 1. It is evident that proposed edge detection algorithm perform well than other methods.



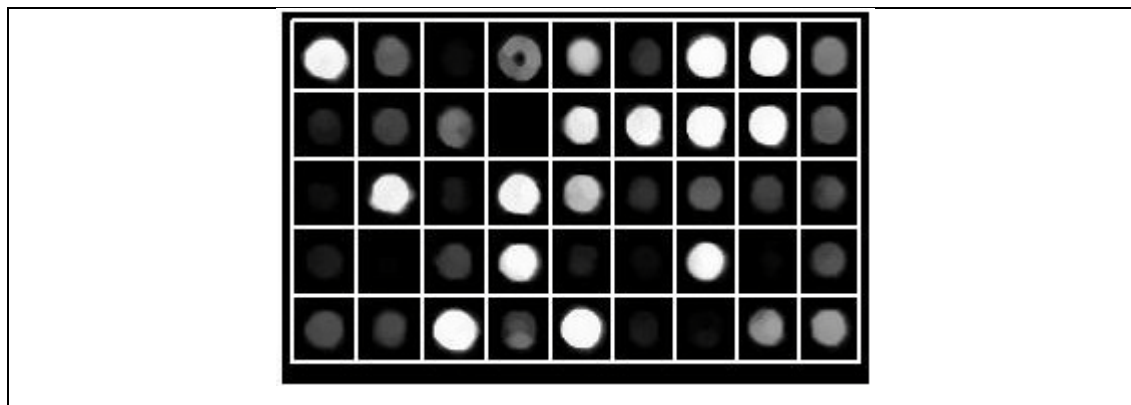


Figure 4: Edge Detection of Microarray Image

Table 1: No. of edge pixels

Operator	Count
Dilation Type	2066
Erosion Type	1906
Dilation-Erosion Type	1889
Proposed	2668

V. CONCLUSION

In this paper, we presented an edge detection of Microarray images using Adaptive Multi-structure Morphological Algorithm. The proposed edge detection technology on separating spots from the background decreases the probability of errors and gives more accurate information about the spots such as pixel number, degree of fragmentation, width and height of the spot, and circumference of the spot. The method is highly adaptive and preserves most of the edge information needed for detection. The proposed method identifies the spots with low density, thus increasing the performance of microarray images. After the guided spots are found, the correct grid can be generated for processing the microarray image.

VI. REFERENCES

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